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INTERNAL DISPARITY: ANALYZING THE ASSOCIATION BETWEEN TRAVEL-TIME-TO-CENTER AND POPULATION DENSITY IN BALTIMORE, MARYLAND

by

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-Mike

Abstract

INTERNAL DISPARITY: ANALYZING THE ASSOCIATION BETWEEN TRAVEL-TIME-TO-CENTER AND POPULATION DENSITY IN BALTIMORE, MARYLAND

Michael Paul Schoelen

The accomplished goal of this study was to further understand if the presence of automobile mass-transit routes have modified the distribution of the Baltimore City population as high density urban areas have grown based upon statistical analysis of population and network datasets. An evaluation of the results supports that Baltimore City's population density is clustered, and that this clustering is, in part, associated with the presence of mass-transit routes, and their ability to lower commute times. This was accomplished through a multi-faceted method, based on extensive literature and allowed for by the use of Geographic Information Science, ultimately allowing for a direct comparison between TTC and population density within the study area. This research is novel and necessary, because of its use of GIS network analysis to understand transportation times, a process which is newly branching.

Keywords: **GIS, Network Analysis, TTC, Urban Sprawl, Land Conservation**

Table of Contents

List of Tables

List of Figures

Section I: Introduction

1.1 Background

When planners constructed the first urban centers, in the forms of key markets or trading ports, civilizations grew concentrically around the essential loci, with each inhabitant attempting to live as close to the center as possible (Meyer and Esposito, 2015; Schoelen and Thebpanya, 2015). Socio-economic standing, cost of goods, and available transportation dictated the distance from the point that any given person could inhabit (Figure 1; Park and Burgess, 1967). With this model, each urban member had equal access to the center, and each strived to live as close to the center as possible. This principle, now known as the Burgess concentric zone model, has been used by researchers to understand the shape and behavior of urban regions since these regions became common-place (Meyer and Esposito, 2015). However, with the mass-transit revolution—first with railways and now with multi-lane automotive highways—citizens were able to live increasingly further from the central point, yet still access it quickly due to the new high-speed access route (Baum-Snow, 2007[a]). This ability to move quickly to the center point while living in the cheaper, exocentric zone outside of the urban mass has since warped the concentric shape of urban zones, resulting in suburban bulges, or "rays," of populations away from the urban center (Baum-Snow, 2007[b]). Some studies have even shown that these new rays can actually decrease the intercentric population density while increasing the exocentric population density along mass-transit routes (Baum-Snow, 2007[b]). This study can add to the existing body of literature, because the 88% of the Maryland population commutes to

work each day by automobile, either public or private (Table 1; Table 2; United States Census Bureau American Community Survey [USCB-ACS], 2013).

Several studies have attempted to understand the reasoning behind this bulging away from the intercentric zone as well as how a newly formed highway can change the shape and population density of an urban area (Figure 2; Miller et al., 2009). A Virginian attempt to exploit this phenomenon has even been proposed, claiming that "[we] must reach a deeper understanding of the forces and processes [that] create our urban areas" to better allocate resources and drive growth (Etienne, 2006, p. 1). As urban zones expand, regional governments need to allocate funds for resources, at times, using predictive models to forecast sprawl. If a model were to simply estimate that an urban region would expand equally and concentrically, governments might allocate funds to improper locations. This method of understanding will allow the proper allocation of resources as the shape of the urban zone reacts to easier access along mass-transit highways. While many urban centers have reacted to the existence of these routes, a currently concentric urban center could benefit from the findings of continued research. This knowledge would allow a community to preemptively understand how new highway access might warp the existing urban shape and internal population density or contribute to urban sprawl (Laidley, 2015). In addition, new research can aid urban planners in preserving and protecting land where new mass-transit highways are proposed. While the previously mentioned research in the field is notable, most studies use mathematics to predict the expansion of urban zones, then empirically examine the relationships in the real-world using census data or surveys (Baum-Snow, 2007[a]). This research is novel for its use of Geographic Information System (GIS) network analysis, a newer branching field, to understand transportation

times. This allows for the actual travel-time-to-center [TTC] to be calculated for thousands of residences in a single process, without surveying individuals about their morning commute.

1.2 Statement of Research Purposes

This particular study seeks to understand if the presence of automobile mass-transit routes are related to the distribution of the Baltimore City population as the urban area has grown. To accomplish this, the study will analyze the relationship between population density and TTC, which calculates the expenditure in time a commuter must face to reach the urban center based on the availability of automobile transit routes. While it is almost certain that other factors should be included in a more robust model, this study seeks only to understand the changing urban shape from the aspect of automotive transportation, since previous studies have concluded that it is the most essential factor (Garcia-Lopez, 2010; Baum-Snow, 2007[b]).

1.3 Hypotheses

The overarching hypothesis of this study is, based on an extensive review of literature and previous studies (Aljoufie et al., 2013; Baum-Snow, 2007[a]; Baum-Snow, 2007[b]; Lee et al., 2013; Schoelen and Thebpanya, 2015), that a notable negative relationship—examined as an *r* coefficient—exists between TTC and population density. It is also hypothesized that the pattern of distribution closer matches TTC's networked pattern as opposed to concentric Euclidean distance—examined with the Kruskall-Wallis test. This supports the argument that mass-transit routes have modified the shape of the

urban mass in Baltimore City in the past number of decades. In support of this, it is further hypothesized that the population density in Baltimore City decreases in a clustered fashion as Euclidean distance from the center increases, not following a random pattern of smooth dispersion. Additionally, it is hypothesized that TTC would play a notable role in a Geographically Weighted Regression (GWR) model.

Section II: Literature Review

2.1 Baltimore City's Urban Area and Transit System

Founded in 1729, The City of Baltimore was established as a key trading port, due to its proximity to the Chesapeake Bay, drawing populations in to live near the harbor (Figure 3). After centuries of history, the current city recently passed a milestone, reaching a population of over 800,000 citizens (USCB-ACS, 2013). In addition, this region sees over 1.3 million payrolled employees in the Baltimore-Towson Corridor annually (Bureau of Labor and Statistics, 2014). Baltimore has been successful at expansion, likely, due to the number of mass-transit highways which feed commuters and residents into the heart of the city; this includes I-70, I-83, I-695, Route 1, and the Baltimore-Washington Parkway. The surrounding region is also home to Baltimore Washington International Airport, further drawing commuters to the region. In 1950, the Baltimore-Washington Parkway was completed, adding a third major roadway to the Baltimore-Washington Corridor, a series of suburban areas and roads connecting the twin cities of Baltimore and Washington D.C. Following the construction, increase populations in this region were seen as cheap land was available with easy commuter access (USCB, 2013). While the city funds a number of public transit options, its success at transporting a large workforce is controversial; a near-failing grade of D was designated to the system in 2015 by the Central Maryland Transportation Alliance [CMTA] (CMTA, 2015). For this reason, public transit was not incorporated into the model, limiting the scope to only automobile transit.

The scope of this study is being restricted to the limits of the city, which encompasses Baltimore's urban area. This cluster is defined by the US Census Bureau as

all zones with a population density higher than 1,000 persons per square mile and all immediately adjacent zones, defined as the urban fringe, with a population density higher than 500 persons per square mile (USCB, 1994). Preliminary examination of the data shows that this urbanized area strongly matches the shape and size of the city limits, defending the reasoning for this scope limitation to only Baltimore City (Figure 4).

2.2 The Concentric Zone Model and the Urban Center

Within a chapter of *The City*, a 1925 manuscript republished in 1967, Ernest Burgess discusses the different zones of urban structure surrounding a central point (Park et al., 1967). This structuring of people around a common center would later become known as the Burgess Concentric Zone Model, serving as an early foundation for understanding why people choose to live where they do around an urban zone (Figure 1). In this early model, a factory zone and central business district, or "the loop" which provided the region with jobs and financial security served as the focal point of the concentric model (Park et al., 1967, p.50). Immediately surrounding this zone are the homes of the lower-class employees who walk to these factories, surrounded further by the wealthier residential zone of the upper-class employees and suburban commuters who enjoy a "thirty to sixty minute *ride* to their place of employment" (Park et al., 1967, p. 50). It can be drawn from this manuscript that given the opportunity, any inner-city dweller would move away from the central point, should finances allow. Burgess is careful to mention that no one format can be applied to every situation. He also mentions that central-bound transportation routes are "complications" that need to be considered, yet they were not explicitly included as a factor (Park et al., 1967, p. 52).

Moving forward to the 21st century, several advancements have been made in mass-transportation, altering the shape of the urban structure beyond Burgess' scope. In a Canadian study, it was found that increased mass-transit in key cities, such as Montreal, has allowed the population to dramatically increase while minimizing commute time; the result has been a gradual derivation from the concentric model (Balakrishnan and Jarvis, 1991). Researchers found similar results in major global studies, including Jeddah, Austin, Toronto, and Washington D.C. (Aljoufie et al., 2011; Baum-Snow, 2007[a]; Balakrishnan, et al., 1991; Sexton et al., 2012). While the concept of an urban central point has remained stable, researchers have built a body of literature, claiming that transportation is having a notable impact on the shapes of cities since those who live within are now able to exodus with the faster commute times. No study of the modification of the urban population distribution in Baltimore City as a result of automobile mass-transit has been performed, especially with the use of GIS network analysis, further justifying the need for this research.

Some scholars argue that the Burgess Concentric Zone Model, occasionally referred to as the Chicago Model, is still applicable to modern society, even in an automotive age (Holcombe and Williams, 2010; Meyer and Esposito, 2015). However, these scholars argue that the same societal distribution exists, even when the shape of an urban region has been warped by infrastructure. Since these studies have diverged from the classic, rounded model set forward by Burgess in his original manuscript (Park et al., 1967), they will not be referenced as supporting or refuting documents in this study, though they are of a high-caliber of research.

2.3 The Use of GIS to Understand Transportation

With the growing availability of technology and data, researchers have begun using GIS as a tool to understand the relationship between transportation and population. Relevant studies have researched correlations between transportation efficiency and employment rates (Wang and Chen, 2015), urban growth and infrastructure interaction (Aljoufie et al., 2011), and even mobility and spatial dynamics (Priemus et al., 2010) over extensive study areas, without the need for qualitative interaction. The reviewed literature has revealed several different approaches to understanding the impact of transportation on the urban structure. In a 2011 study in Jeddah, Saudi Arabia, researchers found that transport infrastructure causes spatial clustering of populations, and it can be considered as the leading factor in population density shifting (Aljoufie et al., 2011). This knowledge was uncovered after using aerial photography to understand changes in land cover while tracking changes in population over the same temporal span. While this study, in essence, has the same goal of the proposed study, the method needs alteration, primarily since the use of aerial photography unsupervised classification based on NDVI on urban areas reveals low confidence ratings in mixed urban/agricultural areas, such as Maryland (Sexton et al., 2013). As well aerial photography only dates back to the 1980's, 30 years after the completion of the Baltimore-Washington Corridor, a major road network. The largest alteration will be the use of census data to monitor urban shift and growth; this allows for a longer temporal span with a higher degree of accuracy, as discussed later in the methods section. The use of GIS to understand the relationship between transportation and population shifting is a newer method; however, success has been found with this method in the reviewed literature (Garcia-Lopez, 2010; Laidley, 2007).

2.4 Urban Sprawl and Its Impacts

This research is directly applicable to the understanding of urban sprawl, or the expansion of an urban zone in a non-dense, inefficient behavior (Ewing, Meakins, Hamidi, Nelson, 2014). While sprawl can be encouraged by poor urban planning and lack of regional restriction on zoning, most studies agree that an increase in mass-transportation is typically reported with a sprawling society (Ewing et al., 2014; Laidley, 2015; Hamidi and Ewing, 2014), justifying the need for continued research. Studies have proposed six dimensions to sprawl: "density, concentration, clustering, centrality, nuclearity, and proximity" (Laidley, 2015, p. 68). From these six dimensions, four that are applicable to the scope of this research will be considered when creating a comprehensive method: density, centrality, nuclearity, and proximity. Clustering and concentration will not be considered since they use socio-economic push and pull factors in their consideration (Laidley, 2015), beyond the scope of this study.

Urban expansion will keep occurring so long as the human population continues to reproduce, leading to obesity, stress, morbidity, and irresponsible land use (Ewing et al., 2014). Continued research in this field might allow planners to build transportation networks in a fashion that encourage condensed growth, leading to a healthier, sustained society.

2.5 Implications of Extended Research

Beyond the output of new knowledge of the urban shape that Baltimore City has taken, continued research in this field is necessary to update an understanding of urban form that can be applied to any major monocentric hub. Furthermore, this research will test

new combined GIS methodologies, founded on extensive reviews of literature, allowing for the update of early 20th century concepts. This can lead urban planners to build healthier, more responsible societies.

Section III: Methods

To fully understand the relationship between TTC and population density, the method was divided into three major parts. First, a network analysis was performed to calculate the travel time to urban center that a commuter would encounter based on a 2010 infrastructure network. In the next step, the 2010 census population data at the census neighborhood level were obtained and entered into a GIS. The data were analyzed for spatial autocorrelation to determine if the clustering of the dataset fell in line with the hypothesis of the study. Since the intermediate step supported the presence of non-random clustering, Parts I and II were then statistically analyzed to find a relationship between TTC and population density changes in the Baltimore City study area. The limitations to consider with this method have also been included, following the results.

Part I: Computing the Travel-Time-to-Center

The value of this research is the use of GIS, particularly service-area network analysis, as a tool for computing the travel time to urban center that any commuter would encounter, rather than mathematical derivation or empirical observation (See Baum-Snow, 2007a). Empirical observations take significant time to observe a wide enough population sample—a sample which is constantly changing, while purely mathematical derivations do not allow for the consideration of geographical context in the data—conserved areas, topography, and other features. The option to use GIS for this study pulls from both options, and provides a direct, real world application of mathematical modeling. This multi-step process required the collection of GIS data from a variety of sources, ranging from official to open-source. The data were processed in a GIS using a service-area

network analysis, and then zonally averaged into a census tract for direct comparison with population density in Part III. Within this analysis, several maps were created to compare travel cost in respect to Euclidean distance, path distance with respect to the network, and TTC with respect to the network *and* speed limit—the defining characteristic of automobile mass-transit, as defined in this study.

3.1.1 Data Collection

While collecting transportation infrastructure feature classes was simple, in this case it was a simple download from the Open Baltimore web portal, collecting speed limit attribute data proved difficult due to the sheer cost. The speed limit information for each street segment was necessary for the network analysis to estimate the expenditure in time for a commuter to reach the city center. As an effective alternative for non-major routes with unknown speed limits, the maximum speed was estimated based upon the provided street type (Table 3). While this method would not be ideal for use in a GPS or emergency response system, it is effective in this study to demonstrate the impact of a limited number of major routes, mentioned earlier. The result provided was a complete transportation network dataset that can be used for a network analysis.

3.1.2 Selecting a Central Region

Using the standing notion that each urban conglomerate includes one central, economic focal point (Park et al., 1967), a center point for the network analysis was selected. A geographic dataset of all commercial buildings within the city was imported to ArcMap 10.2 from the Open Baltimore database (htttp://data.baltimorecity.gov). From here the location of the central most business was identified, using the central feature tool

provided by ESRI. This tool averages the X and Y locations of all input features, in this case point data, and derives the mean center; the nearest input location to the mean is then selected as the central point (Environmental Systems Research Institute [ESRI], 2014). Other methods of calculating the center would include the mean-center calculation and the median-center calculation; however, the use of these methods risks selecting a central location that is not accessible by the transportation network. By selecting an existing business as a central feature, it was guaranteed that the network could access the point. This method results in a single point located at 39.299 N, 76.616 W (Figure 5). The success of this method is supported by the point's coincidence with the Baltimore-Towson Business Corridor, mentioned earlier as a regional economic hub (Bureau of Labor and Statistics, 2014).

3.1.3 Calculating Euclidean Distance to Central Point

To calculate the Euclidean distance to the center, the basic geometric function of Pythagorean's Theorem was applied via a python function in a field calculation. The coordinates of the selected central point was converted to miles by displaying the data as NAD83 State Plane Maryland FIPS 1900. Then the math.hypot() function was applied to calculate the hypotenuse between the centroid of the neighborhood polygon and the central point. This simulates the "as the bird flies" distance between each neighborhood and the central point, ignoring network structure.

3.1.4 Service Area—Network Analysis

The ESRI ArcMap 10.2 service area network analysis tool allowed for the total cost—this study recognizing commute time as a cost—for a driver to traverse each segment

of roadway on the way to a destination to be calculated, given that the fastest possible route is chosen. Consulting with speed limits, this step involved a simple calculation of the amount of time required to traverse each road segment in Baltimore City. These travel time values were then incorporated into a network dataset. From here a service area was computed from the urban center in 1 minute intervals until the edge of the urban area was reached. Once the service area was calculated for the study area, the values were absorbed into a census tract unit field as a value for later comparison. The same process was also completed, disregarding speed limits. This produced the average path distance, or amount of road needed to traverse to reach the center, for each neighborhood.

Part II: Analyzing Population Density within a GIS

To find the population density of a given area, several different methods could have been employed, including remote sensing, empirical observations, and census counts (Sexton et al., 2013, Park et al., 1967, Baum-Snow, 2007[b]). Using remote sensing data to scan for urban areas, researchers use signs of urban life as a proxy for population; the study does not take into account the number of residents within a dwelling, or if a residency is abandoned. Meanwhile, empirical observations would be impossible to cover such a large study area in a limited time with any degree of accuracy. The best data source option, preferred by similar literature, to understand the distribution of the population comes from the United States Census Bureau (Laidley, 2015). This dataset covers the entire study area with high accuracy (USCB, 1994; USCB-ACS, 2013).

3.2.1 Census Data Collection

The United States Census Bureau has created an efficient site for data collection in a number of different formats, including shapefile, tabular, and geodatabase. The census neighborhood data from the most recent 2010 surveys were obtained from the Open Baltimore data portal—relayed from the main U.S. Census data archive (http://census.gov/geo/maps-data/)—and then imported into ArcMap 10.2. A choropleth map was created for later statistical analysis in Part III.

3.2.2 Units of Analysis

Choropleth mapping is the process of displaying tabular data in a spatial format using grouped blocks (ESRI, 2014); this study displayed population density over neighborhoods or census blocks. While the census provides data at multiple scales, the census neighborhood level was chosen for this study. Preliminary tests with the data demonstrated that a lower spatial resolution at the county level failed to provide enough data to draw a conclusion. Meanwhile, a higher spatial resolution at the census block level resulted in an erroneous output due to low processing power, and a dataset was too large to trouble-shoot. This level of detail was otherwise unnecessary for the study, because the focus is not on individual neighborhoods, but rather the entire county—using census terminology, Baltimore City is considered at the county level of data management. The last distinction to make is the use of census neighborhoods, rather than census tracts. It is important to note here that in the study area, census tracts and neighborhoods are nearly identical in spatial resolution and geographic distribution. The difference is neighborhoods provide a meaningful name to the result, “Fells Point” for example, rather than a census ID

number. Since this study wishes to add to a base of knowledge, the addition of meaningful names will aid city planners who wish to incorporate this study into their work.

3.2.3 Testing for Spatial Autocorrelation with Respect to Distance from Center

Before attempting to understand the relationship between TTC and population density, it was necessary to first examine if Baltimore's population falls into a concentric pattern. In order to support the main hypothesis, the population density would dissipate as distance increased from the center, however there would be a greater amount of clustering in a non-random fashion. This clustering would be attributed to, based on the literature, the presence of automobile mass-transit routes (Aljoufie et al., 2011; Baum-Snow, 2007[a]; Balakrishnan, et al., 1991; Sexton et al., 2012).

To accomplish this, area covered by water was masked from the procedure. Then a buffer was created around the central point in one-mile intervals up to four miles from the center—going beyond four miles results in a radius that extends beyond the boundary of the study area, resulting in significant null values. The neighborhood-level, population density dataset was then clipped to each of the four concentric rings. Individually, Moran's I-Spatial Autocorrelation was run, using a tool provided by ESRI (2014) resulting in a report for each ring. This report includes a Moran's index value, a measure of clustering, and a z-score, a measure of data distribution. Using these two values, the tool derives the level of clustering or randomness present in the dataset.

Part III: Relationship Analysis

The ultimate goal of performing this analysis was to understand the relationship between the presence of automobile mass-transit routes and the distribution of the population density in the surrounding zone. This relationship can be understood from two approaches: qualitative observation and statistical understanding (Park et al., 1967; Baum-Snow, 2007b). A dual approach (3.6 and 3.7) was suitable for this analysis, where observations were made, then supported with basic statistical analysis.

3.3.1 Qualitative Observation

The simplest method of understanding the relationship between TTC and population density was a simple observation between the resulting choropleth maps from Part I and Part II. In laymen terms, the modern TTC will be compared to the 2010 population density distribution in the study area. This showed the relationship between population density and TTC, supporting the argument that the new mass-transit highway was one of the major causes of an increase in population density in the surrounding area.

3.3.2 Statistical Analysis

A more comprehensive understanding of the relationship of the variables includes some level of statistical analysis, as found in most literature on this topic (Aljoufie et al., 2011; Baum-Snow, 2007a; Garcia-Lopez, 2010). Understanding that only a relationship analysis needs to be performed to draw a viable conclusion, a Pearson's Correlation (r) was used initially. To further explore the relationship between TTC and population density, Geographically Weighted Regression (GWR) was also run, with population density as the dependent variable and TTC as the independent variable. The results of this analysis will,

unlike correlation analysis, illustrate how much variability in population density is accounted for by TTC.

Neighborhood data was also exported and tabularized to create summary tables of the population density and total population. The data was then aggregated by both TTC and Euclidean Distance to center. These aggregated datasets were evaluated using the Shapiro-Wilk test for normality, then the Kruskal-Wallis (K-W) to determine if population density differed across the distance groups. The same tests were run for both population density (Appendix B) and total population (Appendix C). Because this study is focused on the relationship between the designated variables, only the basic results from these tests are mentioned in the upcoming results section. Detailed explanations can be found in the referenced appendices.

Section IV: Results

4.1 Travel Time to Center

Immediately upon performing the network analysis, interesting patterns were observed. The most notable, yet not surprising, observation was that the network does not allow for equal travel time to center. In the Euclidean distance map (Figure 6), concentricity is observed due to the direct line calculation. The variation from perfect circles is due to the zonal calculation into the census neighborhood level of measurement. Likewise, concentricity is observed in the path distance map (Figure 7), albeit with slightly more irregularity than the previous map. The dramatic observed shift from concentricity is observed when the rate of travel is accounted for (Figure 8 and Figure 9). Rays begin to pull away from the center mass, with reductions in speed along the outskirts of the center mass—this is symbolized by the addition of the dark blue category for distances not needed in Figure 7. The presence of high speed automobile transit routes are responsible for these rays. This demonstrates that even at the urban level, mass-transit routes are significantly altering the TTC variable over relatively short distances of a few miles. For example, this phenomenon exists in two neighborhoods in the central north portion of the city. In the neighborhood of Roland Park along Route 83, it is possible to reach the urban center in about 7.5 minutes. Comparatively at the same Euclidean distance from center, the neighborhood of Ramblewood experiences a commute time of about 10 minutes. This differential of about 2.5 minutes is attributed to the difference in access to automobile mass-transit routes, demonstrating that travel time is not uniform within the urban area.

4.2 Dispersion of Baltimore City's Population

Likewise, the analysis of the population distribution revealed interesting patterns. Neighborhoods in Baltimore experience a wide range of population densities—from 63 residents per square mile in the north central portion of the city to 47,768 residents per square mile in the heart of Downtown Baltimore (Figure 10). While this large range is interesting, this study focused on the distribution and clustering of that population, like the population corridor seen extending north to south in the upper portion of the city. Results from the spatial autocorrelation analysis by distance demonstrate that as Euclidean distance from the center increases the population becomes more clustered (Figure 11). For example, within 0 to 1 miles of the city center, the population density exhibits a z-score of *0.4985* and a Moran's Index value of *0.0283*. From these two values, the data can be designated as random, or not following a particular pattern of clustering. In comparison, between 3 and 4 miles from the urban center, a z-score of *2.98331* and a Moran's Index of *0.1066* are observed, denoting a highly clustered pattern. An examination of figure 10 reveals how the population tends to cluster near mass-transit routes, with the exception of Northern I-83 (Jone's Falls Expressway). Due to this portion of interstate's proximity to Jones Falls, a large portion of the land is designated "Local Protected Lands" by the state of Maryland, and urban build up is limited (Maryland Department of Natural Resources, 2016). The remainder of the data from this analysis can be found in Table 5.

4.2.1 Population Density and the TTC Aggregation

As mentioned in the methods section, the Shapiro-Wilk tests calculated that the population density was not normally distributed in the TTC categories (Table 6). This

aggregation shows a decline in mean population density as network distance from the center increases. The post-hoc results from the TTC aggregation show that population density tends to be higher in zones with a low TTC, and lower in zones with a high TTC. This effect becomes more significant past the 5.5 minute range. When running the aggregate samples against total population, rather than population density, the K-W test did not show significant differences between the groups. Similar analyses were completed for population density per Euclidean distance category, total population per TTC category, and total population per Euclidean distance category. The results of these analyses can be found in Appendix B and Appendix C.

4.3 Relationship between TTC and Population Density

Once it was determined that the population distribution in Baltimore City exhibited differential clustering, the next challenge was to determine the direction and strength of the relationship between TTC and Population Density—this can speculatively understand if the presence of mass-transportation routes could be designated as an influential variable. Calculating Pearson's *r* coefficient between TTC and Population density indicated that there was a moderate, negative correlation between the two variables, $r = -0.43$, $n = 254$, $p < 0.001$.

When the TTC variable was applied alone to model population density, a GWR R^2 value of *0.37* was produced. This indicates that 37% of the variance in population density can be explained by the independent variable. The residuals map from this analysis (Figure 12) allow for the geographic understanding of where the built model overpredicted—over reaching the impact of TTC as a variable—or underpredicted with the given variable. At a

reach, the model overpredicted values along automobile mass-transit routes, while underpredicting values in areas with limited automobile mass-transit routes—though no pattern applies to the whole study area. The majority of the city is consumed with neutral residual values, denoting a level of model success.

Drawing from these results, a census neighborhood with a low commute time (TTC) will likely experience a higher population density, supporting the stated hypothesis. These findings support Baum-Snow's (2007[a]) model, as well as the 1964 model on which he based his research (Alonso, 1964).

Section V: Discussion

The results from these analyses allow a glimpse into an existing relationship between travel time and the density of a given population, in this case Baltimore City. Analyzing the neighborhood distance from center in three forms (Euclidean distance, path distance, and TTC), first gave the understanding that Baltimore's transportation network is not uniform. While two neighborhoods could exist at an equal Euclidean distance from the center and with the same drive distance, the actual travel time can vary significantly. Meanwhile, this study understood the pattern of dispersion that Baltimore City exhibits. The population density is radial, dispersing outward from the selected urban center. However, clustering was observed with growing significance as Euclidean distance from the center increased. This draws two inferences: The population is not concentrically distributed in Baltimore City and that there is most likely a variable at play that is causing this clustering.

At this point, two datasets are in-hand: a travel network with growing inconsistencies in TTC as Euclidean distance from center increases, and a population distribution that grows in clustering as that same Euclidean distance increases. Evaluating the Pearson's correlation coefficient of *-0.43* between these two variables infers that a moderate negative relationship exists between the variables. In neighborhoods with a low TTC, we could expect to find a relatively higher population density than a nearby neighborhood with a high TTC. Running GWR with these variables gives the understanding that other variables are certainly at play. However, it also denotes that the variable of TTC might be responsible for over 30% of the variation in population density—

this signifies that it is a paramount variable to incorporate in a model attempting to model population distribution. The analyses of variance performed also suggest that the population density follows the pattern laid by TTC more than a concentric distribution (Appendix B). The use of total population in variance analysis gave no insight in this study—this is because census neighborhoods keep a fairly steady total population between groups by keeping inconsistent total areas (Appendix C). Population density is the better measurement of population dispersion. While many studies referenced in this research, Baum-Snows 2007[a] article in particular, focus on how highway construction is linked to suburbanization, this study has found that a significant relationship also exists within the urban area. This exemplifies that urban regions are not only growing, but internally altering.

These results would suggest that if an automobile mass-transportation route were constructed near a neighborhood that previously had a low TTC, the population density in that region would be expected to increase. This raises some interesting perspectives on the additional effects of highway building on conservation. For example, if a highway were built along a conserved land, the development value of that land could increase due to the desirability for homeowners and renters to quickly access the urban center (Miller et al., 2009). This could give pressure for homeowners to overturn conservation easements on their land due to the lands increased value, a startling possibility revealed in a legal article aptly named *[…] Till Legislation, Do We Part* (Brewer, 2011). On both sides of the aisle, policy makers and developers could use this information to benefit.

5.1 Limitations

There are countless other factors at work which influence the changing structure of urban regions, not limited to gentrification, increasing education, changing family structure, and the use of transportation beyond automobiles (Balakrishnan et al., 1991). These factors were not considered here, because transportation availability has a strong relationship with the shape of urban zones (Baum-Snow, 2007[b]; Aljoufie et al., 2011).

Because such a broad area was considered in this study, the use of open sourced data was necessary. Where possible, officially credited data was used, however estimated data supplemented it—as was the case with speed limit data. Sound methods were used to estimate this data, and the estimation was based upon official street type classifications. This analysis also does not account for the stopping time necessary at each road crossing, nor does it consider one-way street segments; however this would only exacerbate the finding that highways allow for faster transportation to the urban central point, since these impediments are only located on inner-city roadways.

5.2 Opportunities for Future Research

While it is understood that a one-variable model based on mass-transportation availability is not robust enough to completely predict the spatial patterns of a future population, a model could be built using additional variables and compared to the current distribution of the population in future research. This would then allow for a community and policy makers to understand how a population distribution might react to the construction of a new mass transit route. Additionally, a study might incorporate these

findings to understand if the presence of mass-transit routes have caused land prices to increase as a response to increased desirability.

Section VI: Conclusion

The accomplished goal of this study was to further understand if the presence of automobile mass-transit routes have a relationship with the distribution of the Baltimore City population based upon statistical analysis of population and network datasets. An evaluation supports that Baltimore City's population density is clustered, and that this clustering is, in part, associated with the presence of mass-transit routes, and their ability to lower commute times. The results yielded a notable negative relationship between TTC and population density, thereby supporting the argument that the automobile mass-transit routes have modified the concentric shape of the urban mass in Baltimore City.

The study was accomplished through a multi-faceted method, based on extensive literature and by the use of GIS, ultimately allowing for a direct comparison between TTC and population density within the study area. This research is novel and necessary, because of its use of GIS network analysis to understand transportation times, a process which is newly branching.

Urban zones are expanding at a rate which would have shocked the early researchers in this field; it is estimated that by 2025, 58% of the world's population will be living in an urban zone (World Bank, 2015). Models which fail to account for the role of transportation in effecting population density will result in poor fund allocation, and potentially the loss of conserved area. This method of understanding accounts for the reaction of the urban zone to easier access along mass-transit highways, ultimately aiding planners in understanding the future shape of the urban region.

Appendices

Appendix A: Operational Terminology and Definitions

Concentricity: Behaving in a radial fashion, with population density diminishing equally in all directions from the central point.

Exocentric: An area outside the main, concentric mass of population density.

Travel-Time-to-Center (TTC): The amount of time, in minutes, for a commuter to reach the selected urban center using the network at the posted speed limit.

Urban Area: A grouping of neighborhoods with a relatively higher population than the surrounding neighborhoods.

Urban Center: A locational average of all commercial zones in the study area.

Appendix B: Analysis of Data Variance (Population Density)

Normality was tested using the Shapiro-Wilk test. This method tests whether the distribution in the input population matches a normal distribution. The Kolmogorov-Smirnov test would also accomplish this, but this study's sample size of less than 2000 elements mandated the use of the Shapiro-Wilk test. This test showed that the population density was not normally distributed in either of the aggregations (Euclidean or TTC). This mandated that the chosen variance test—in this case, the Kruskal-Wallis [K-W]—manage abnormally distributed inputs. In both cases, the K-W test was significant, requiring post-hoc analysis to compare each in-group category to determine where key differences are present. The results were then compared between these tests to determine if the population better fit a concentric distribution, or a distribution matching automobile mass-transit route availability.

The Shapiro-Wilk tests calculated that the population density was not normally distributed in either of the aggregation categories—Euclidean distance from center, nor TTC. From here, the results significantly vary in the K-W tests between the two groups. In Euclidean distance aggregation, post-hoc tests demonstrate significant differences between categories *3 and 2*, *3 and 4*, and *4 and 2*. This denotes that as the Euclidean distance from the center increases from the urban center, the population distribution begins exhibit significant differences between the groups. Meanwhile, the post-hoc results from the TTC aggregation show significant differences between categories *3 and 1*, *3 and 2*, *4 and 1*, *4 and 2*, and *5 and 1*. This splits the data into two groups: categories *1* and *2*, and categories *3*, *4*, and *5*. This shows that population density tends to be higher in lower numbered

categories, and lower in higher numbered categories. This effect becomes more significant past the 5.5 minute (category 2) range. The data from these tests can be found in Tables A-F, below.

Table A: Shapiro-Wilk test of normality with Euclidean distance as the independent variable

	Shapiro-Wilk			
	Euclidean Distance	Statistic	df	Sig.
Population Density for Euclidean Distance	1	0.801	21	0.001
	2	0.958	71	0.019
	3	0.967	74	0.05
	4	0.956	95	0.003

Table B: Kruskal-Wallis test of normality with Euclidean distance as the independent variable

Total N	261
Test Statistic	34.294
Degrees of Freedom	3
Asymptomatic Sig. (2-Sided test)	0

Table C: Post-Hoc Kruskal-Wallis test of normality with Euclidean distance as the independent variable

Sample 1- Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
4.00-3.00	32.514	11.704	2.778	0.005
4.00-1.00	39.928	18.203	2.194	0.028
4.00-2.00	68.957	11.842	5.823	0
3.00-1.00	7.414	18.664	0.397	0.691
3.00-2.00	36.443	12.54	2.906	0.004
1.00-2.00	-29.03	18.751	-1.548	0.122

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptomatic significances (2-sided tests) are displayed. The significance level is .05

Table D: Shapiro-Wilk test of normality with TTC as the independent variable

		Shapiro-Wilk		
	Euclidean Distance	Statistic	df	Sig.
Population Density for TTC	1	0.812	53	0
	2	0.955	80	0.006
	3	0.929	93	0
	4	0.96	96	0.005
	5	0.945	46	0.03

Table E: Kruskal-Wallis test of normality with Euclidean distance as the independent variable

Total N	368
Test Statistic	85,597
Degrees of Freedom	4
Asymptomatic Sig. (2-Sided test)	0

Table F: Post-Hoc Kruskal-Wallis test of normality with Euclidean distance as the independent variable

Sample 1- Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
5.00-3.00	22.196	19.175	1.158	0.247
5.00-4.00	28.802	19.075	1.51	0.131
5.00-1.00	101.333	21.436	4.727	0
5.00-2.00	138.102	19.684	7.016	0
3.00-4.00	-6.606	15.477	-0.427	0.67
3.00-1.00	79.137	18.308	4.323	0
3.00-2.00	115.906	16.221	7.145	0
4.00-1.00	72.532	18.204	3.984	0
4.00-2.00	109.3	16.103	6.787	0
1.00-2.00	-36.768	18.84	-1.952	0.051

Appendix C: Analysis of Data Variance (Total Population)

As in Appendix B, normality was tested using the Shapiro-Wilk test. This method tests whether the distribution in the input population matches a normal distribution. The Kolmogorov-Smirnov test would also accomplish this, but this study's sample size of less than 2000 elements mandated the use of the Shapiro-Wilk test. This test showed that the total population was not normally distributed in either of the aggregations (Euclidean or TTC). This mandated that the chosen variance test—in this case, the Kruskal-Wallis [K-W]—manage abnormally distributed inputs. In both cases, the K-W test was not significant. The results from these analyses can be found in tables G-J.

Figure A evaluates why significant differences might not be visible when using total population for variance analysis. Because the area of a census neighborhood can vary, it is possible to have two groups with the same total population and very difference total densities (neighborhoods 1 and 3, in Figure A). For this reason, the data provided in Appendix B is a better indication of the distribution of Baltimore City's population.

Table G: Shapiro-Wilk test of normality with Euclidean distance as the independent variable

	Shapiro-Wilk			
	Euclidean Distance	Statistic	df	Sig.
Total Population for Euclidean Distance	1	0.668	16	0
	2	0.782	62	0
	3	0.766	64	0
	4	0.777	87	0

Table H: Kruskal-Wallis test of normality with Euclidean distance as the independent variable

Total N	229
Test Statistic	2,901
Degrees of Freedom	3
Asymptomatic Sig. (2-Sided test)	0.407

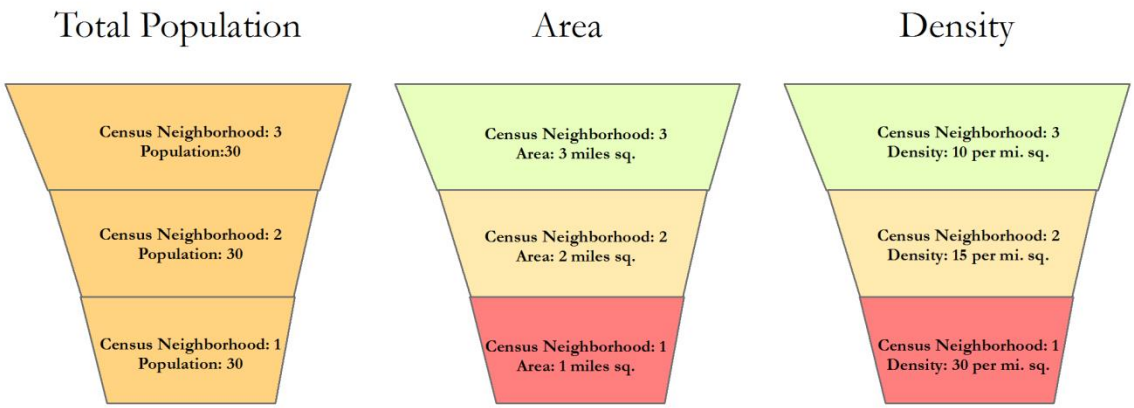
Table I: Shapiro-Wilk test of normality with TTC as the independent variable

	Shapiro-Wilk			
	Euclidean Distance	Statistic	df	Sig.
Total Population for TTC	1	0.753	45	0
	2	0.859	68	0
	3	0.787	81	0
	4	0.794	96	0
	5	0.512	45	0

Table J: Kruskal-Wallis test of normality with Euclidean distance as the independent variable

Total N	335
Test Statistic	5,607
Degrees of Freedom	4
Asymptomatic Sig. (2-Sided test)	0.28

Figure A: The impact of neighborhood area in the evaluation of Total Population vs. Density (from Appendix C)



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Tables

Table 1: Average Modes of Transportation for Maryland Residents
(USCB American Fact Finder, 2007)

Subject	Maryland				
	Total		Male		Female
	Estimate	Margin of Error	Estimate	Margin of Error	Estimate
Workers 16 years and over	2,891,357	+/-7,397	1,467,135	+/-4,350	1,424,222
MEANS OF TRANSPORTATION TO WORK					
Car, truck, or van	83.5%	+/-0.2	84.5%	+/-0.3	82.5%
Drove alone	73.5%	+/-0.2	74.3%	+/-0.3	72.6%
Carpooled	10.0%	+/-0.1	10.2%	+/-0.2	9.9%
In 2-person carpool	7.7%	+/-0.1	7.5%	+/-0.1	7.9%
In 3-person carpool	1.3%	+/-0.1	1.5%	+/-0.1	1.2%
In 4-or-more person carpool	1.0%	+/-0.1	1.2%	+/-0.1	0.8%
Workers per car, truck, or van	1.07	+/-0.01	1.07	+/-0.01	1.07
Public transportation (excluding taxicab)	8.9%	+/-0.1	7.9%	+/-0.2	9.8%
Walked	2.4%	+/-0.1	2.4%	+/-0.1	2.4%
Bicycle	0.3%	+/-0.1	0.5%	+/-0.1	0.1%
Taxicab, motorcycle, or other means	0.8%	+/-0.1	0.9%	+/-0.1	0.7%
Worked at home	4.2%	+/-0.1	3.9%	+/-0.1	4.5%

Table 2: Average Commute Time for Maryland Residents (USCB American Fact Finder, 2007)

TRAVEL TIME TO WORK					
Less than 10 minutes	8.1%	+/-0.1	7.2%	+/-0.2	8.9%
10 to 14 minutes	9.8%	+/-0.1	9.2%	+/-0.2	10.5%
15 to 19 minutes	12.5%	+/-0.2	11.8%	+/-0.2	13.1%
20 to 24 minutes	13.2%	+/-0.2	12.7%	+/-0.2	13.8%
25 to 29 minutes	6.0%	+/-0.1	5.9%	+/-0.1	6.1%
30 to 34 minutes	15.1%	+/-0.2	15.7%	+/-0.3	14.5%
35 to 44 minutes	8.9%	+/-0.1	9.3%	+/-0.2	8.4%
45 to 59 minutes	11.8%	+/-0.1	12.3%	+/-0.2	11.4%
60 or more minutes	14.6%	+/-0.2	15.8%	+/-0.2	13.3%
Mean travel time to work (minutes)	32.0	+/-0.1	33.2	+/-0.1	30.7

Table 3: Estimated Speed Limits based on Street Type

Street Code (Open Baltimore)	Street Type	Estimated Speed Limit (MPH)
STRALY	Ally	25
STRPRD	Road	30
STRR	Highway	50
STREX	Interstate	65
Other	*Other*	*35*

Table 4: General statistics about the Baltimore City study area, 2010

Population Statistics	
Total Neighborhoods	289
Total Population	622,104
Average Neighborhood Population*	2481.172077
Max Neighborhood Population	17694
Min Neighborhood Population*	18
Population Standard Deviation*	2479.011005
Average Density* (per sq. mile)	11685.01006
Minimum Density* (per sq. mile)	62.50907361
Maximum Density* (per sq. mile)	47767.66943
Standard Deviation*	7427.220565

*Excludes census neighborhoods with 0 population

Table 5: Results from Spatial Autocorrelation Analysis by Distance

Distance from Center	Moran's Index	Z-Score	Pattern Determination
1	0.028339	0.498555	Random
2	0.161131	1.90787	Mildly Clustered
3	0.231721	3.0674402	Highly Clustered
4	0.106661	2.98331777	Highly Clustered

Table 6: Population density aggregated by TTC, 2010

Population Density Statistics by Travel Time to Center					
TTC *(Minutes)*	Group Class For Stat. Analysis	Minimum Density (per sq. mile)	Maximum Density (per sq. mile)	Mean Density (per sq. mile)	Standard Deviation
0 - 3.5	1	2562.837265	47767.66943	14484.69305	7815.571447
3.5 - 5.5	2	3200.461571	34452.81132	17268.58529	7394.917818
5.5 - 7.5	3	248.0192095	23453.38036	9192.509272	6430.833884
7.5 - 9.5	4	62.50907361	27203.30267	9595.263813	5724.787747
9.5 +	5	66.13152802	21906.07127	7714.063605	4013.424216

Figures

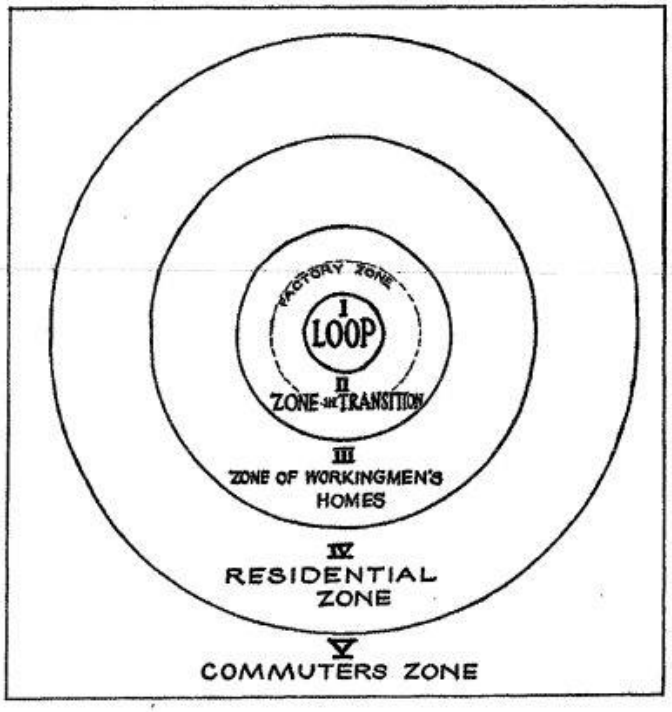


Figure 1: Burgess Concentric Zone Model (Source: Park et al., 1967).

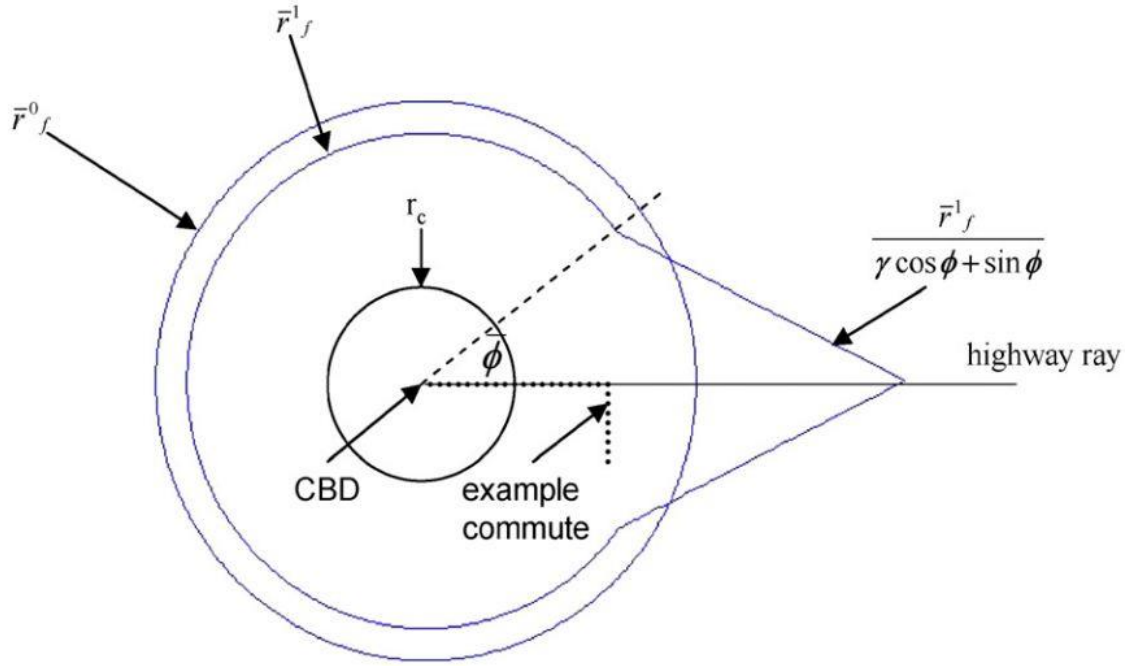


Figure 2: The expansion effect of a new highway on an existing urban mass
(Source: Baum-Snow, 2007[a])

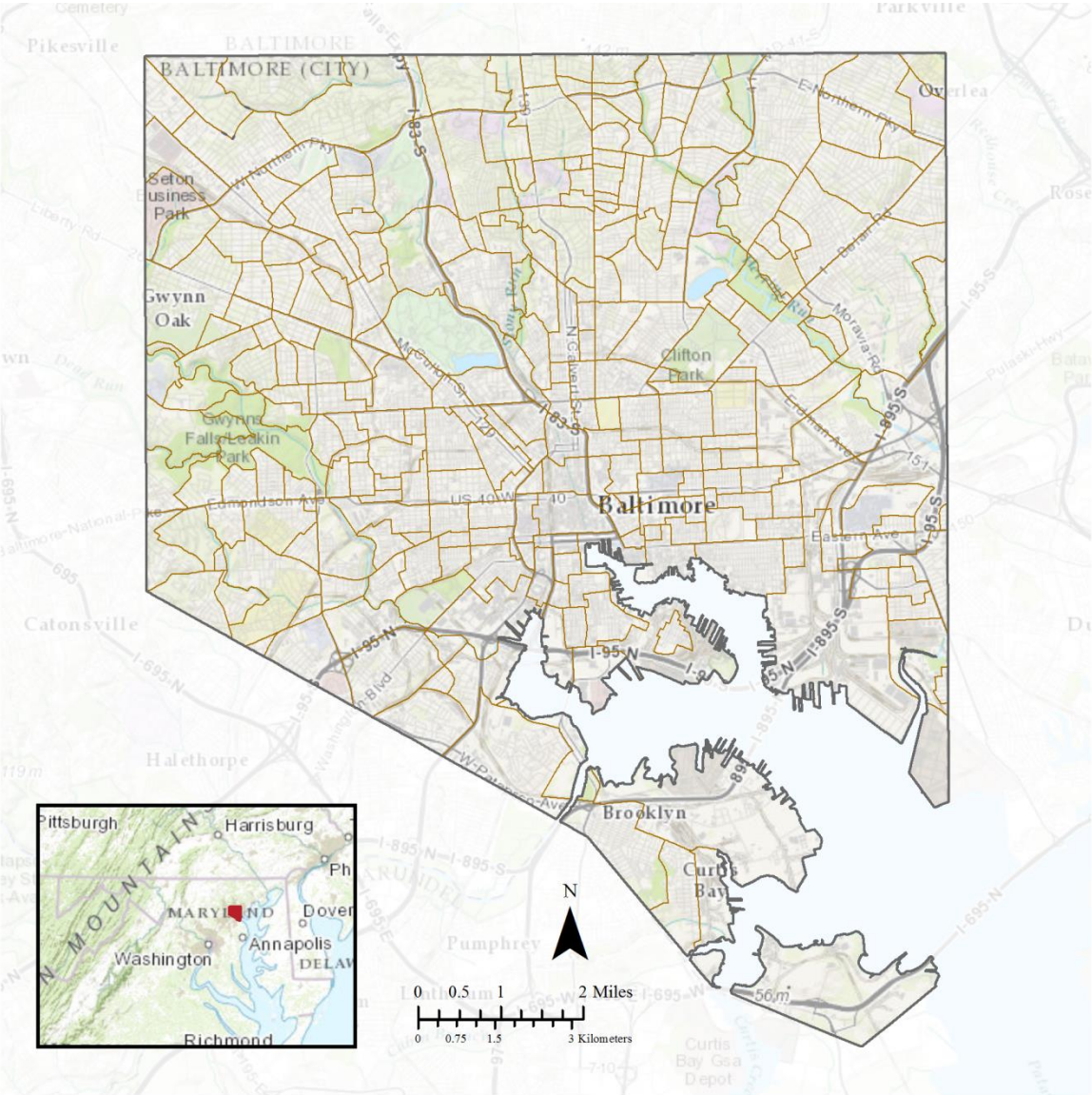
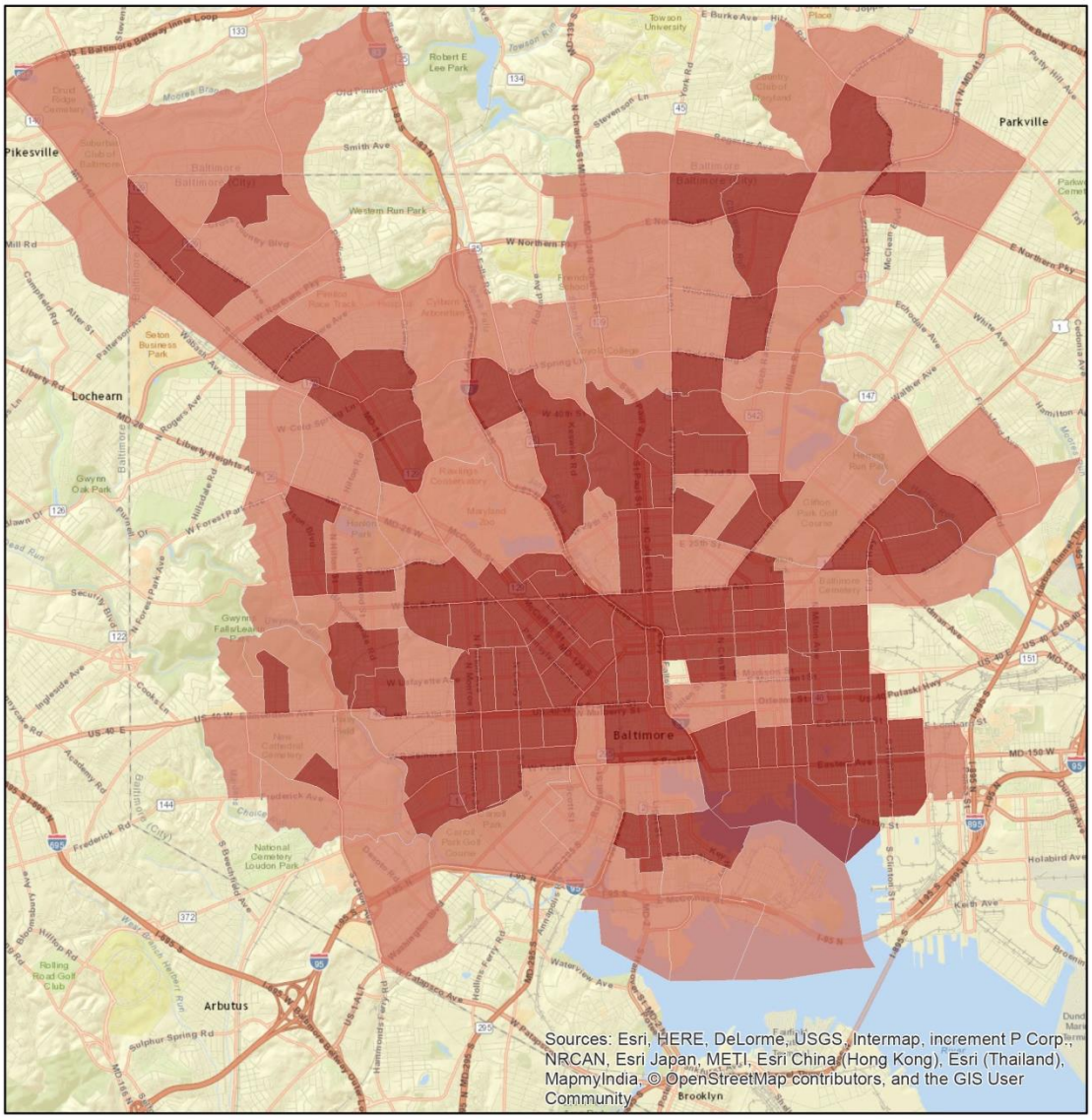


Figure 3: The Baltimore City study area, delineated by census neighborhood



Legend

Tract_2010Census_DP1 selection selection selection

DP0180001 / Area_Mi2

- Non-Urban Cluster(<500 Residents/sq mi.)
- Surrounding Urban Cluster(500-1000 Residents/sq mi.)
- Urban Cluster (>1000 Residents/sq mi.)

Figure 4: Baltimore's urban area as defined by the US Census Bureau (USCB, 1994).

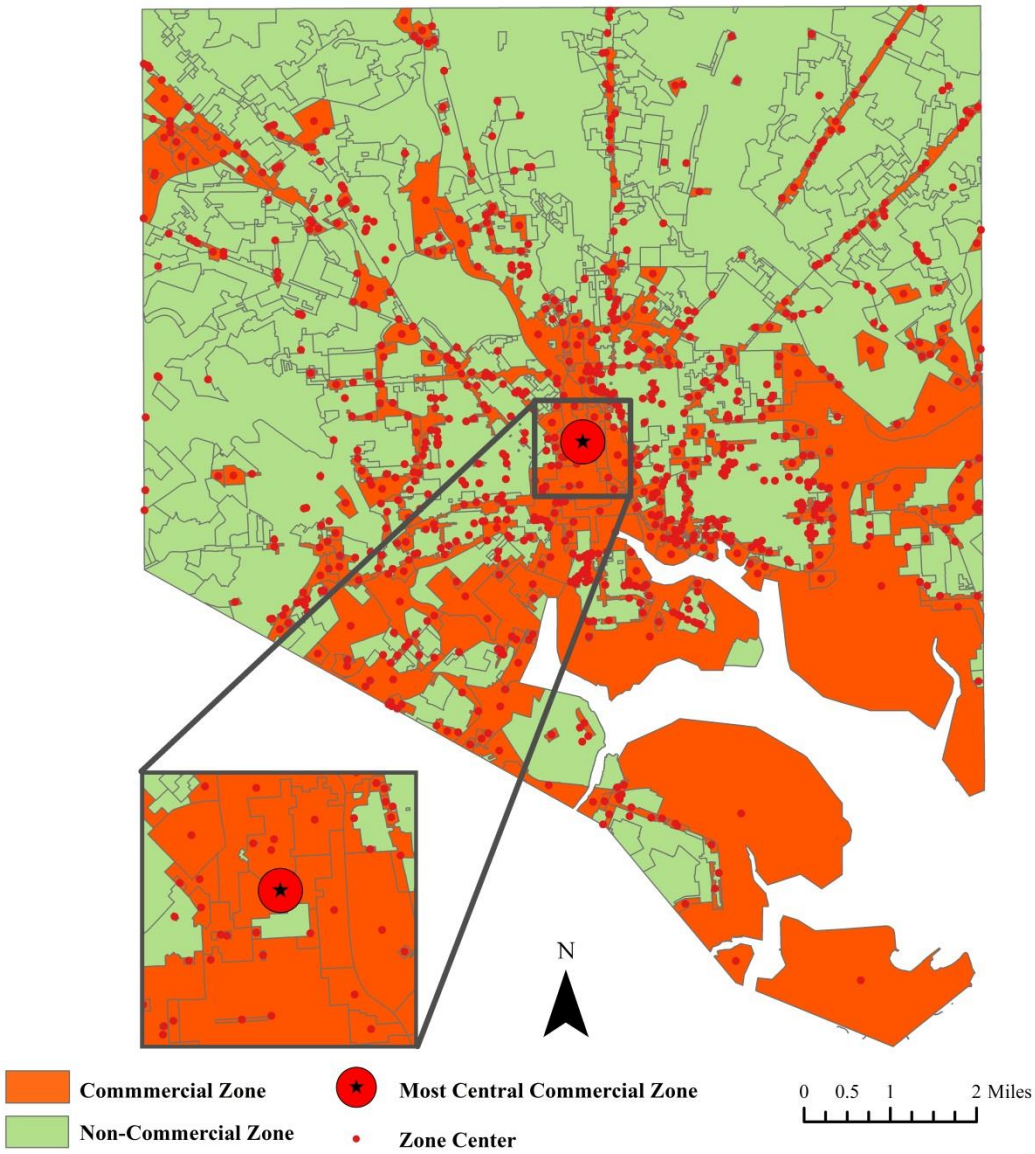


Figure 5: Selecting a Central Point for Network Analysis,
Baltimore, MD 2010

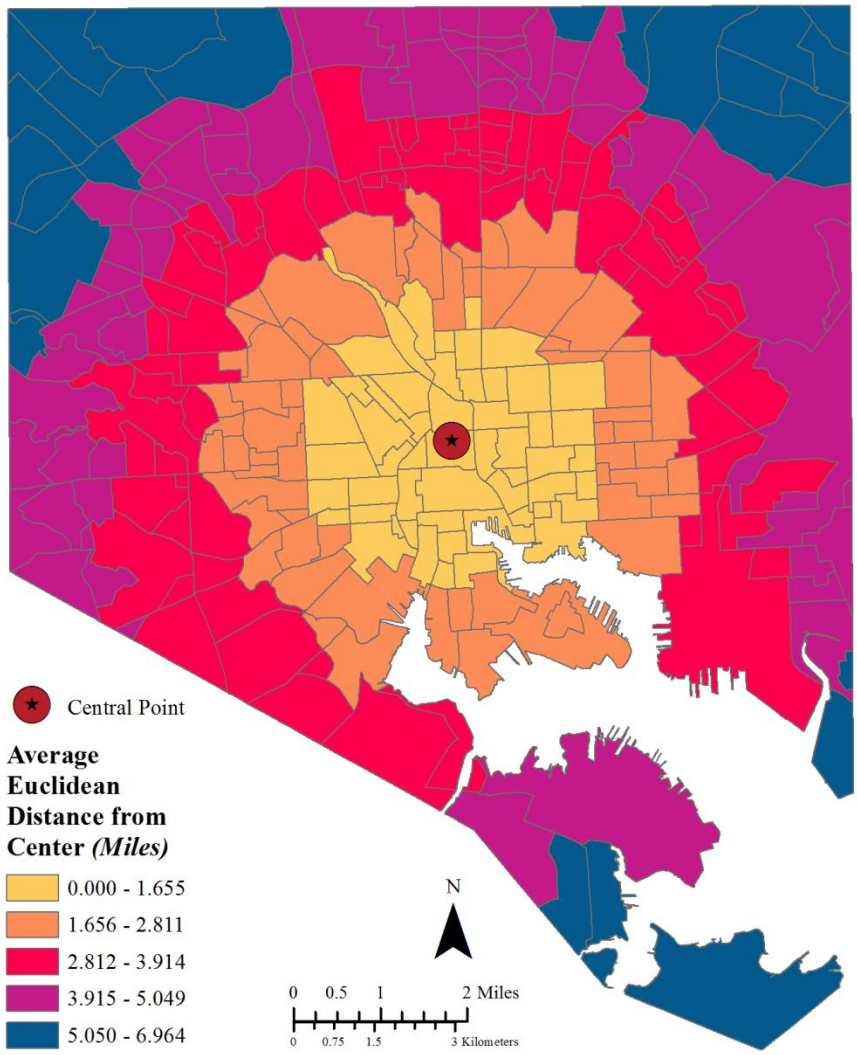


Figure 6: Average Euclidean distance from each neighborhood to the selected central point, Baltimore, MD 2010

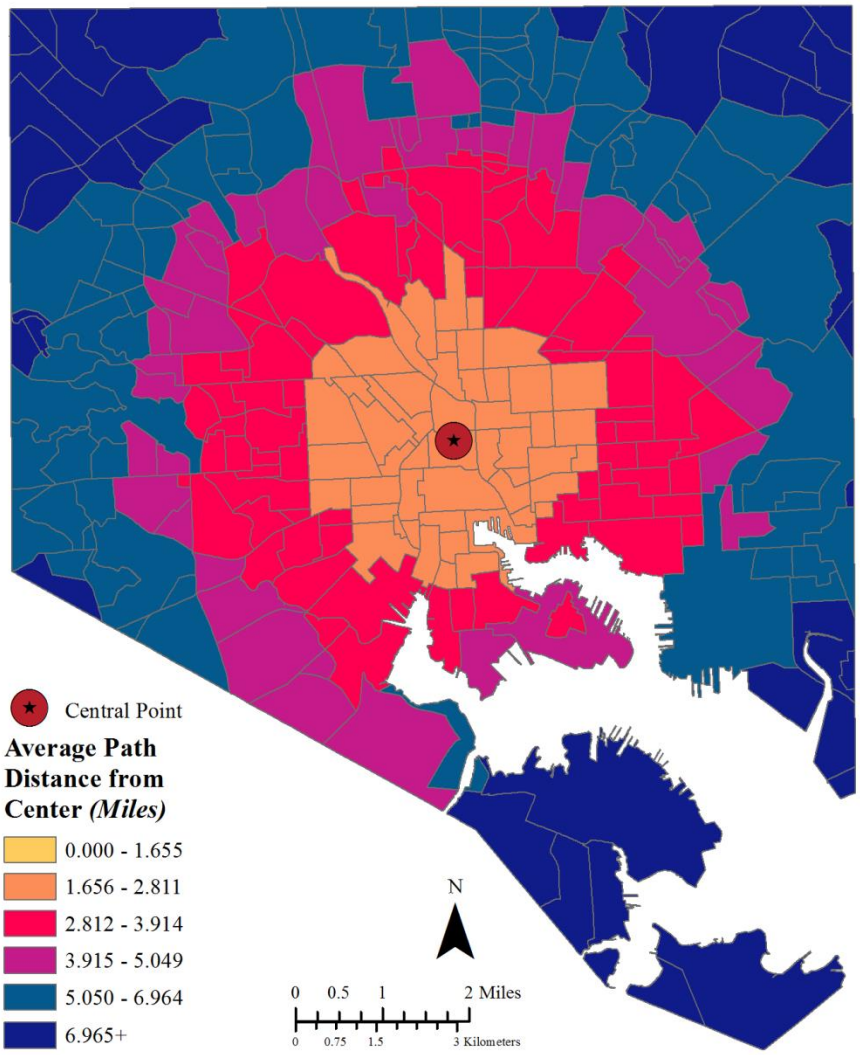


Figure 7: Average neighborhood path distance via network to reach the selected center, Baltimore, MD 2010

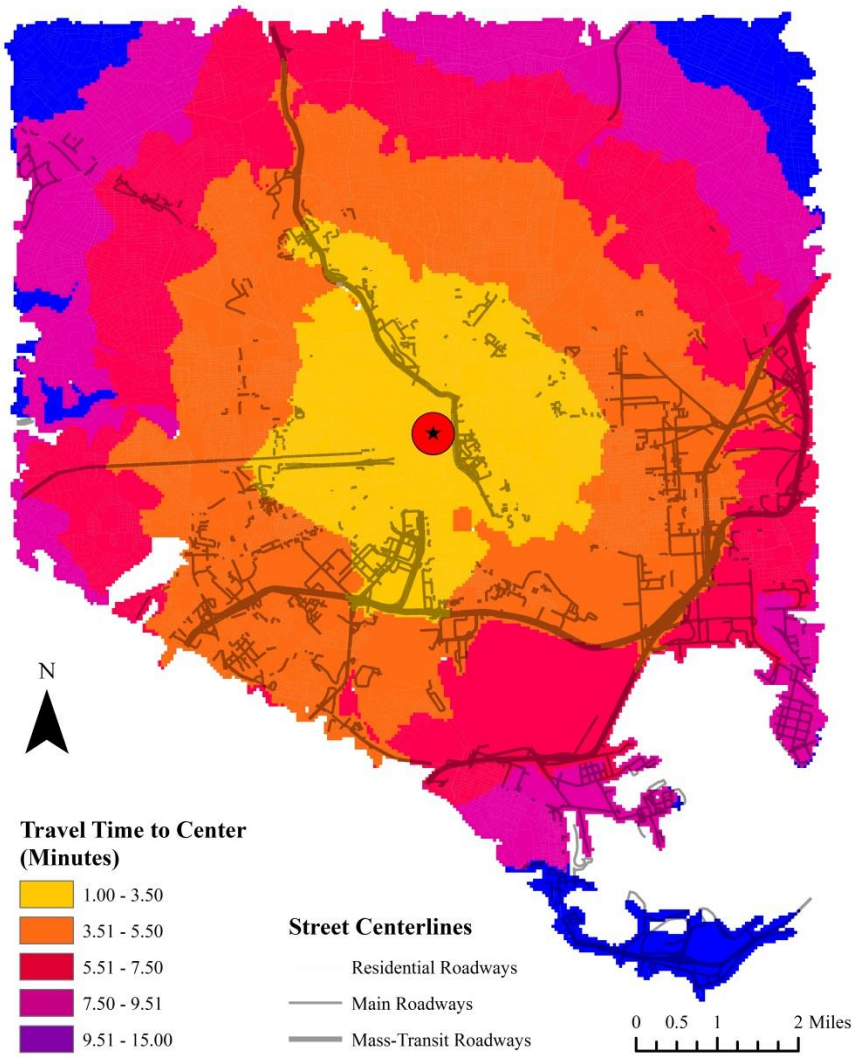


Figure 8: Reverse service area, demonstrating TTC, Baltimore, MD 2010

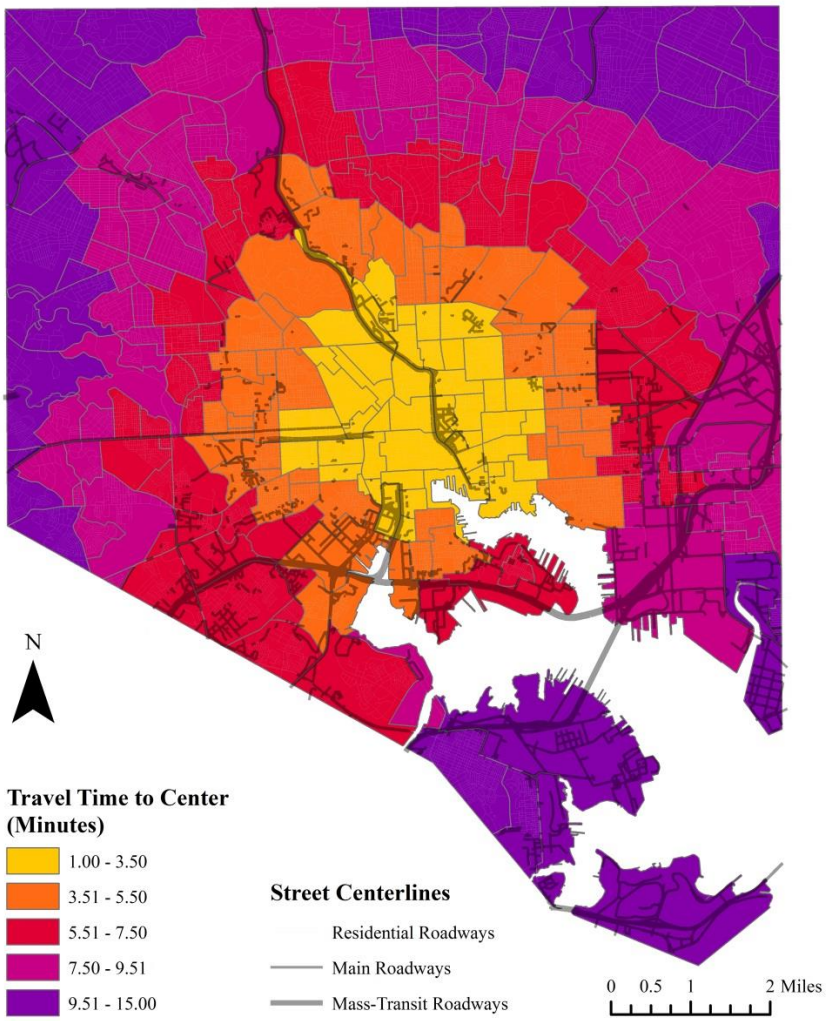


Figure 9: TTC, by census neighborhoods, Baltimore, MD 2010

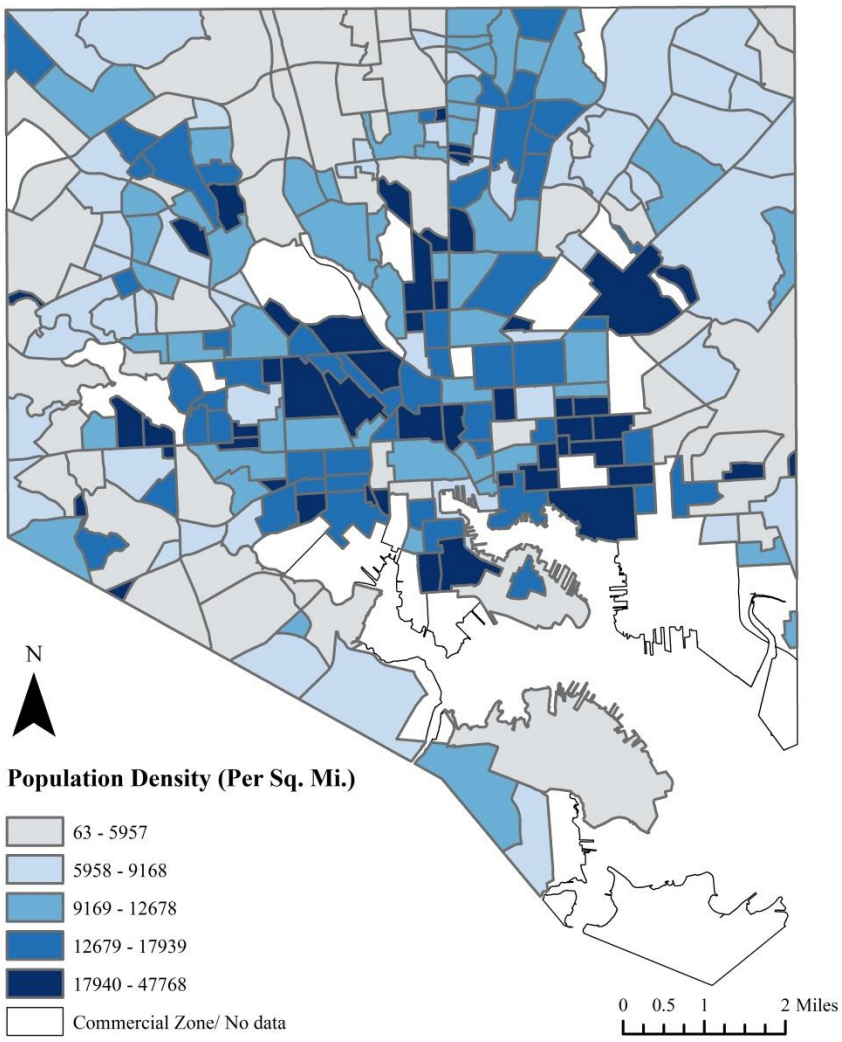


Figure 10: Population density by census neighborhood, Baltimore, MD 2010

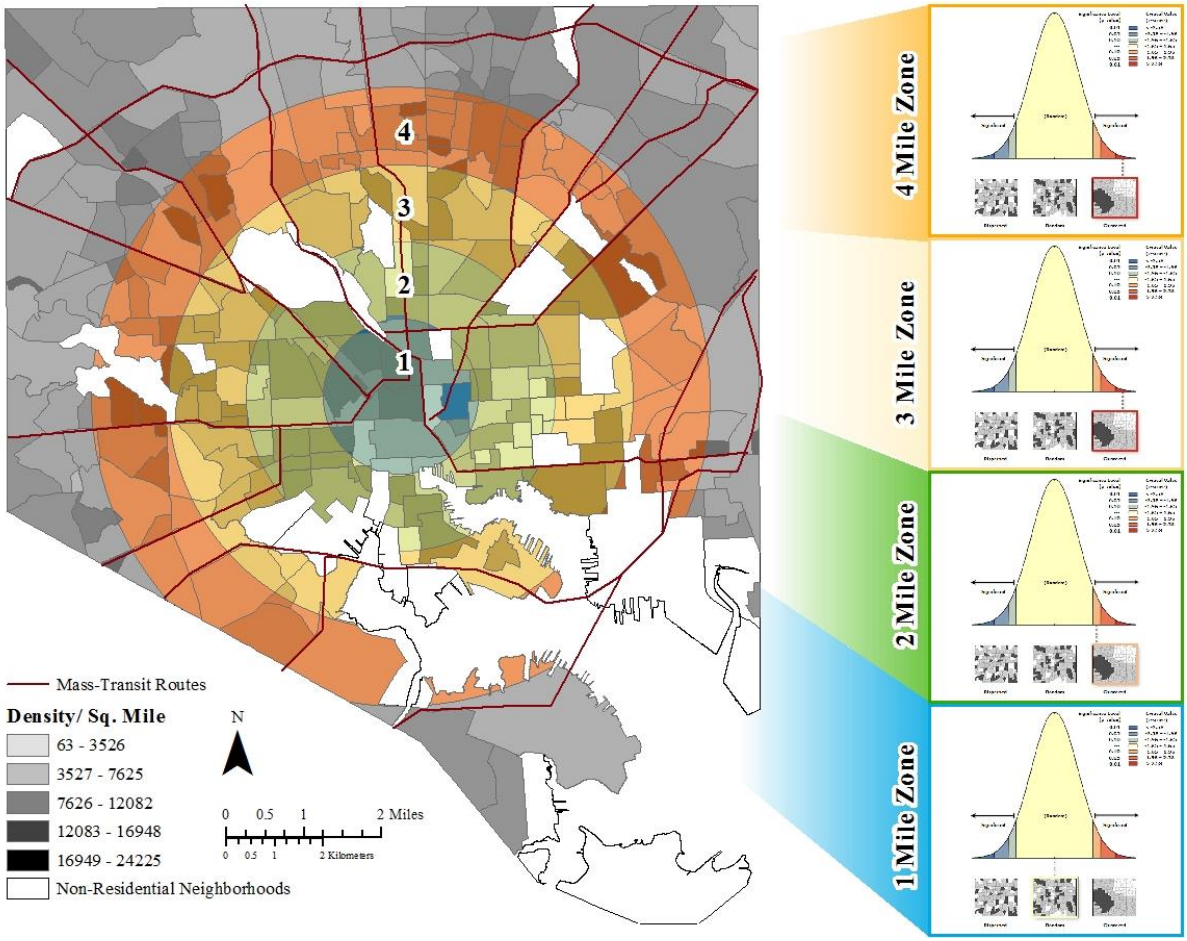


Figure 11: Dispersion of Baltimore City's population in relation to Euclidean distance from center. Clustering can be observed around mass-transit rounds (highlighted in red), Baltimore, MD 2010.

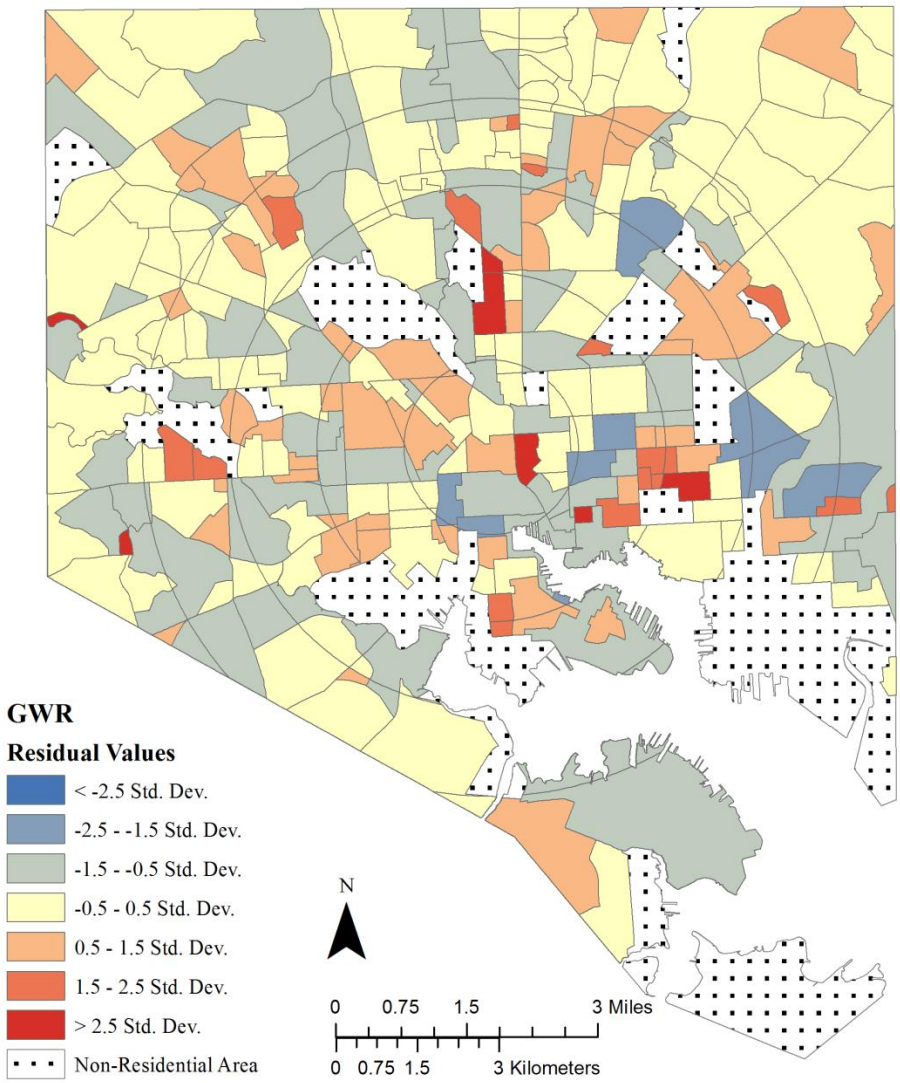


Figure 12: Geographically Weighted Regression residual values. In this model, population density serves as the dependent variable with TTC as the independent variable. Baltimore, MD 2010

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"As a premise, I make the assumption that everything is related to everything else…"
-Waldo Tobler

Education

- **TOWSON UNIVERSITY**/ May 2016/ Geography and Environmental Planning/ Masters Candidate/**3.97**
  Relevant Coursework: G.I.S. Database Design, Applied G.I.S. Intelligence Briefing, Seminar on Geographical Perspectives, Applied Climatology, Hydrology, Remote Sensing with Python Programming, and Research Methods.
  Academic Achievements:
  2015 Towson University Alumni Association Graduate Student Fellowship Award
  2015 Philip Lee Phillips Society Post-Graduate Research Fellowship
  Graduate Teaching Assistantship 2014-2015
  2015/16 Towson University G.I.S. (TUgis) Conference Volunteer Coordinator
- **FROSTBURG STATE UNIVERSITY**/ May 2014/Environmental Analysis and Planning/ Bachelors/**3.41**
  Relevant coursework: G.I.S., Technical Writing (including grant writing experience), Applied Calculus, Biogeography, Geographic Data Handling, Advanced Remote Sensing, Environmental Planning/ Law, Physical/ Human Geography, Digital Image Analysis/Processing, Applied Probability.
  Academic Achievements:
  Cum Laude
  2014 EVAP Departmental Honors
  Presidents Leadership Circle
  Emerging Leader Award, Social Change Award, SGA Outstanding Senior Award

Professional Experience

- **DEPT. OF DEFENSE/** Integrated Biosurveillance GIS Administrator [CTR]/ December 2015-Present
  Under the Armed Forces Health Surveillance Branch, this role required the creation of regular interval map products, both static and dynamic, as well as the innovation and testing of new map products and GIS data management techniques to convey messages to public and federal clients about global health activities.
- **THE LIBRARY OF CONGRESS**/ GS-5 Post-Graduate Research Fellow/ June 2015–December 2015
  This role required innovation to update a mass-collection of 2.5 million paper maps to the new digital, Geographic Information System (GIS) standard. Challenges were constantly faced and overcome as new systems, scripts, web mapping, and automation procedures were implemented. New procedures needed to be created and simplified to allow use by non-technical employees. This required adaptation to pair new methodologies with existing structures.
- **BALTIMORE COUNTY DEPT. OF PUBLIC WORKS**/ GIS Analyst Intern/ January 2015–May 2015
  Primary data collection, processing, and quality control/assurance of urban information, including signage, flood plains, and traffic calmings. It is often necessary to devise new processes to solve changing issues, including writing python scripts, using Microsoft excel functions, and using the latest ESRI ArcMap 10.2 tools. All new processes were recorded and used to educate others on how to solve future issues.

Skills and Additional Experience

- Extensive ESRI ArcGIS 10.3 experience
- Functional scripting skills for GIS and simplified web mapping (Python, Microsoft Visual Basic, JavaScript)
- Extensive MS Office Suite experience
- Technical writing skills with peer-review experience
- Extensive experience in team-based leadership positions
- International experience (Peru, Uganda, Kenya, United Kingdom)
- Eagle Scout with Gold Palms