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Spatial and Temporal Assessment of Regional Crime

A Dissertation submitted in partial satisfaction of the

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in Geography

by

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Spatial and Temporal Assessment of Regional Crime

For Versie Mae, Nina Ann, Rebecca Nicole, and Heather Jeaneen.

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Computer and Network Systems Analysis

ABSTRACT

Spatial and Temporal Assessment of Regional Crime

by

Crystal YeVonne English

The analysis of crime events has advanced beyond simple pin maps. It incorporates both basic spatial statistics and more complex computational methods for pattern and density discovery. Unfortunately, visualization has lagged behind algorithmic methods and techniques. This has contributed to a lack of standard procedures for data visualization in criminology and crime analysis (Maltz 2014, 5581). The addition of a temporal component adds to the complication, as it continues to create difficulty with the interpretation of space-time phenomena. When comparing crime across different regions, visualization is further confounded by the different methods in which data is collected and maintained by the respective local government agencies, like the police and city planning departments.

There are several known attractors of crime, like drug markets, bus stops (Block and Block 1995; Brantingham and Brantingham 1995; Weisburd and Green 1995; Hart and Miethe 2014), and specific land use concentrations (e.g. bars, motels and public housing). Current cluster visualization methods (e.g. point density and kernel density estimation) are limited in their approach to revealing hidden attractors of crime across space and time. The purpose of this study is to develop computational, multi-dimension geospatial and temporal attribute data models to discover hidden crime attractors in institutionalized, high-density

cluster locations — meaning areas where a high-density of crime events has persistently occurred over ten or more years.

Crime data from 2004-2013 collected from three police jurisdictions were combined with non-police data (e.g. census and transportation) to answer the following questions: (1) What geographic factors are highly correlated with reported crime and are these factors spatially and temporally similar each year? (2) Which locations of persistent high-density crime cannot be explained by the factors revealed in Q1; and, what types of mapping and visual analytic methods can be used to discover additional factors? (3) How can the factor-based methods used to answer Q2 be used to explain spatiotemporal patterns of crimes both over time and across/within the three cities?

This work was expected to enhance crime analysis methodology by testing and validating data analytic methods for temporal and attribute visualization from a geographic perspective, thus informing knowledge discovery.

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1.1 Statement of the Problem

The first application of a geographic framework for crime-pattern discovery and analysis in the United States is generally attributed to August Vollmer, Chief of Police in Berkeley, California. Between 1906 and 1909, Vollmer developed techniques using recorded calls-for-service “to perform beat analyses” and used maps “for visually identifying areas where crime and calls were concentrated” (Gottlieb, et al. 1994, 2). His colleague O.W. Wilson later enhanced the work by weighting crime categories according to the severity of the crime, providing a systematic approach to the allocation of police resources (Gottlieb, et al. 1994).

Since then, the analysis of crime events has advanced beyond simple pin maps. It incorporates basic spatial statistics and complex computational methods for density discovery. Unfortunately, visualization has lagged behind algorithmic methods and techniques. This has contributed to a lack of standard procedures for data visualization in criminology and crime analysis (Maltz 2014). Essentially, creating meaningful images representative of crime data analyses has not been standardized across the domain of criminology nor in the field of crime analysis. The addition of a temporal component adds to the complication, as it continues to create difficulty with interpretation of space-time phenomena. When comparing crime across different regions, the ability to illustrate differences and similarities is further confounded by the varied methods in which data is collected and maintained by the respective local government agencies, like the police and city planning departments. Moreover, how do we determine what viable solutions are applicable to a problem if only a few years of data are examined at any given time?

How I propose to address these issues is to use previously developed methods of analysis in a collaborative manner to better evaluate space-time associations in attribute and geographic space. By incorporating regression and temporal analytic methods, and illustrative mapping and graph techniques, I hope to derive greater insight from long-term, high-density crime locations. Such an approach would be an improvement over previous approaches, as the study would examine more than a two- or three-year period of data in each location, thus presenting the possibility of developing new insights into long-standing, high crime areas that would otherwise be difficult to observe.

1.2 Research Questions

This study focuses on spatial and temporal relationships between violent and property crime events, the places in which these crimes occurred, socioeconomic factors and land use types. Three cities in different regions included in this research are Atlanta, Georgia; Chicago, Illinois; and Seattle, Washington. The specific types of crimes to be studied include street robbery, aggravated assault, residential burglary, and auto theft. Those crime types were selected because they have a much higher propensity for containing precise geolocation information and there are higher frequencies of incidents, which provide better samples for analysis.

This work addresses the following key questions from a crime analysis perspective:

1. For the regional policing jurisdictions to be studied, what geographic factors are highly correlated with a change in reported crime and are these factors spatially and temporally similar for all three cities?

2. Which persistent clusters of crime cannot be explained by the factors revealed in Q1? For the identified locations, what types of mapping and visual analytic

methods can be used to discover additional factors?

3. How can the factor-based methods used to answer Q2 be used to explain spatiotemporal patterns of crime both over time and across/within the three cities?

1.3 Objectives

To answer the research questions, analyses was performed at three resolutions: 1) citywide, 2) neighborhood areas, and 3) block-level/street segments. Block-level census data obtained via FactFinder is messy and requires quite a bit of cleaning to collate all of the tables into a single database for query. This was particularly the case for the city of Atlanta because the city resides in two different counties, is discussed in greater detail later in the Data and Methods chapters.

The purpose of this study was to develop multi-dimension geospatial and temporal attribute data models to discover hidden crime attractors in persistent (or institutionalized), high-density clustered locations across geographic regions. Such models were expected to be a significant improvement on current models, which tended to examine one- or two-dimensional space-time phenomena, like analyzing crime in one location over a few years or analyzing crime in several locations within the same city over a few years.

What this study intends to reveal is that clustered crime patterns in some locations, though they may be thousands of miles apart, are more similar than those patterns immediately adjacent to them. In other words, it may be the case that distant locations have a much closer relationship to each other in attribute and temporal space.

Chapter 2. Background

2.1 Crime and Geography

A geographic approach to crime, rather than a purely statistical method, was generally used to determine the social and physical factors most correlated with crime rates from 1902 to 1941 (Cohen 1941). In that respect, physical elements were not considered to be direct, primary causal influences. However, climate and seasonal influences were noted as factors that led to an increase in crime. Specifically, “crimes against persons [were] more numerous in the summer [and] crimes against property [were] more numerous in the winter” as noted in Cohen’s review of nineteenth century studies of climate and crime (1941, 30). Weather and climate have been used in more recent studies to explain crime trends (Ranson 2014; Gamble and Hess 2012; and, Hsiang, Burke and Miguel 2013).

Some advances in the analysis of crime and crime patterns within the field of geography have occurred since criminologists first began considering geography when analyzing criminal incidences. Researchers leading this innovative charge were not from the discipline of geography, but in the field of criminology. Furthermore, scholars in departments of sociology, mathematics, and psychology have continued to move forward in the refinement of established theories and the development of new models with direct application to the analysis of crime events. However, those approaches are often mired in complicated mathematical computations that are generally ineffective for solving practical ‘real-world’ issues of crime, as well as lacking in the coherent visualizations of findings.

The span of research has examined many social aspects of an urban community and related them to the causes of crime. Lowman (1986) sought to “[separate] crime from the control of crime” (81). He also argued that “geographers have been unjustifiably selective in their use of criminological theory in developing geographic prospective on crime" (81) That is to say, in general, geographers have chosen to view criminal events and crime prevention through a singular lens (e.g. Social Disorganization), rather than adopt a multi-theoretical approach that addresses crime events and the response to those events separately. In the years following, geographers seem to have made little headway in the rectification of that observation. Such studies have tended to lean towards the generalized conceptions of minorities living in low-income urban centers as possessing a greater predilection towards the commission of crime than those in a minority or non-minority status, living in middle-class and upper-class communities. Geographers have also tended to follow the theory of delinquency developed in the Chicago School of Sociology (Shaw, Zorbaugh, McKay, and Cottrell 1929). Unfortunately, as Lowman stated, "If geographers were to produce maps of crime including white collar, governmental, and corporate offenses, they might find that the classic central city-to-suburb criminal residence gradient was quite different." (1986, 86).

Although this study does not incorporate federal-level offenses or corporate crimes, it does adopt a multi-theoretical, cross-disciplinary approach in its analyses. By employing an integrated conceptual framework that uses discipline-based methods and approaches, it is possible to examine the problem of longitudinal analysis and mapping methods for crime-pattern detection and neighborhood vulnerability and approach lines of inquiry from a different perspective.

2.2 Theories in Geography

Theories of crime as they relate to geographic information and the spatial sciences are varied. From a positivist perspective, the introduction of statistics and quantitative methods into geographic analysis was important. A scientific approach was thought to be more accurate than a narrative method, which was the standard before formalized quantitative methods were adopted in the field of geography (Gaile and Willmot, 2003). For this study, a combination of quantitative and qualitative methods provided the best approach given the use of nominal and ordinal data, as well as interval and ratio data sources. The qualitative method primarily used for this study is the collection and use of imagery to perform both inductive and deductive analyses of identified areas with long-term high levels of crime.

2.2.1 Regional Science

When considering geography, space, time and regional analysis, it is important to reflect upon Hägerstrand's paper regarding regional science (1970). In his presidential address to the Association of American Geographers, Hägerstrand brought to the attention of regional scientists the notion of small-scale theoretical analysis, alluding to the lack of such research being conducted. If regional research was to continue informing policy and planning, then it was important to understand what was occurring at the micro-level, rather than only examining aggregate macro-level data.

Essentially, assumptions made at the macro level may not be the same on a micro scale. For example, when doing research on economic recovery at a national level, findings may point to a positive trend – meaning recovery is happening, whereas the same research at a county or municipal level may show level or negative trends – meaning no recovery or the economy is still in decline.

Hägerstrand (1970) introduced the concept of space-time nodal network analysis at the micro socio-economic level, indicating that individuals are tied to space and time. While this was at the time a rough theoretical outline, spatial-temporal research continues today, with a specific focus on nodes and networks. Moreover, with computer advances, computational models are easier to construct, making analyses faster and more reproducible.

This study uses regional analysis, and analyses at the micro scale.

2.2.2 Spatial Interaction

Spatial interaction can be generally defined as human-involved movement over space. This movement "includes journey-to-work, migration, information and commodity flows, student enrollments and conference attendance, the utilization of public and private facilities, and even the transmission of knowledge" (Haynes and Fotheringham 1984, 9).

A fundamental aspect of spatial interaction, from a scientific geography perspective, is the gravity model. This model allows for relative locations rather than absolute location information, meaning although two locations may have a precise latitude and longitude and be exactly the same distance apart, the two locations may be vastly different in terms of amenities. Using an example similar to one illustrated by Haynes and Fotheringham (1984), it is possible to talk about two locations, each being five miles from an urban area. The first is five miles from Los Angeles, California, the second is five miles from Lincoln, Nebraska. While the two distances are absolute, the relative locations have markedly different amenities, which would draw an individual or group to one or the other. Thus, the gravity model plays a specific role in making such decisions.

A gravity model has two basic components: 1) scale impacts – e.g. cities with large populations tend to generate and attract more activities than cities with small populations; and 2) distance impacts – e.g. the farther places, people, or activities are apart, the less they interact (Haynes and Fotheringham 1984). Although the gravity model has been used in many disciplines from archeology (Clark 1979; Hallam, Warren and Renfrew 1976; Jochim 1976) to linguistics (Trudgill 1974), gravity models are more widely used these days in business and transportation studies to explain the movement of commodities and the behavior of consumers. For example, why would a shopper travel a greater distance to an outlet shopping mall when there is a Westfield branded mall less than two miles away? While both locations offer similar amenities, the first location presumably has those amenities at a much lower cost.

Gravity models were not explicitly used in this study; however, it was important to explain spatial interaction in such a way as to be able to reflect upon the concept during analysis. Gravity models have been used in areas other than econometrics to include immigration (Lewer and Van den Berg 2007).

2.2.3 Spatially Integrated Social Science

Spatially Integrated Social Science is rooted in the notion that “a wide variety of social processes and problems are understood more clearly through the mapping of phenomena and the analysis of spatial patterns” (Warf 2006, 484). Its concepts include spatial association, which links information sets, social processes and problems to geographic coordinates and regions. The principle of place-based analysis allows for the use of data and methods to analyze a specific place using diverse geographic information, which is one of the primary principles this study uses

2.3 Theories in Criminology

As law enforcement agencies and academics have attempted to explain the causations of crime and the psychology of criminal offenders, various theories were developed based upon different methods of analyses. Those theories include Social

Disorganization Theory and several interrelated theories considered to be under the topic of Environmental Criminology – Routine Activity Theory, Rational Choice Perspective, and Crime Pattern Theory. There are also schools of thought which include the Cartographic School, the Chicago School and the GIS School. These explanations of crime events were designed to provide researchers and practitioners with concepts to better understand not only how incidences of crime occurred, but also where they tended to happen and the factors leading to repeated events (English 2013). The two most commonly applied theories are social disorganization and routine activity because they are readily adaptable to qualitative studies and do not necessarily require a mapping or visualization component. More recently, the GIS School and Environmental Criminology have been heavily used as they involve quantitative research and cartographic visualization of crime.

2.3.1 The Cartographic School

The Cartographic School of Criminology was established by L.A.J. (Adolphe) Quetelet and André-Michel Guerry in the early nineteenth century. The two were social criminologists who used statistics to explore the "influence of social factors such as season, climate, sex, and age on the propensity to commit crime" (Cordella and Siegel 1996, 8). Guerry, a Frenchman, used maps as early as 1833 to show the distribution of violent and property crime across jurisdictions of France (Chainey 2021). It was their work, along with Emile Durkheim, another social criminologist, that led to other studies into the patterns of crime and criminal behavior. Quetelet's work was ground-breaking as it identified many of the connections between crime and social phenomena which still serve as a foundation for criminological study today (Cordella and Siegel 1996).

2.3.2 The Chicago School

The University of Chicago Department of Sociology was the cornerstone of sociology scholarship in the early nineteenth century. Those contributions were heavily involved in the research areas of community study and criminology (Abbott 1997). Criminologists Clifford Shaw and Henry McKay focused their work on juvenile delinquency in Chicago, Illinois. Their hand-drawn maps became the foundation for mapping sociocultural triggers of crime as Chicago underwent great economic growth (Chainey 2021). The two scholars were the developers of Social Disorganization Theory (1942), which is further explained in the next section.

2.3.3 Social Disorganization Theory

Social disorganization theory was developed in the Chicago School of Social Sciences by sociologists, including Robert Park (1915) and Ernest Burgess (1924). The theory suggested that society operated as an organism, where growth and change is a natural process – similar to what occurs in nature. They viewed the division of urban space into separate social areas as naturally occurring and any disruption of that organized process, like people or businesses moving into or out of a neighborhood, could cause a breakdown in the normative social and moral behavior of the community (1925). Shaw and McKay updated the theory (1942), and made it well known by applying it to juvenile delinquency in urban centers of Chicago. The two authors built upon much of the work of Park and Burgess (1925), who defined social disorganization as an inability of a group to engage in self-regulation. Park and Burgess also developed the Concentric Zone Theory (1925), which stood as a pillar of the Chicago School for decades. The theory posited that a fully-grown city would resemble the form of five concentric rings with areas of social and physical deterioration concentrated near the center, and affluent areas on the fringes of the outer rings. Their position was that a neighborhood's economic status, meaning wealthy or impoverished, was a greater determining factor of criminal behavior than ethnicity, race, or religion (1925).

Social disorganization theory using a concentric application has failed when used for any urban area not in the mid-west or the east. The design of neighborhoods following the push west changed with the availability of more land and urban sprawl. Moreover, it was not generally the case that the city center was where people with lower incomes would migrate. As the city center added more amenities to attract the wealthy, like luxury high-rise residential buildings, the idea of using concentric circles no longer fit the description of the urban landscape in the west. The theory is also not applicable to any area outside of the United States. For example, Dear and Flusty (1998) criticized the continuance of Chicago School theories, though with a bit of derision, because of its "beguiling simplicity and the enormous volume of publications produced by adherents of [the school]" (Dear and Flusty 1998). Dear and Flusty were part of the Los Angeles School of Urbanism, which had its beginnings in the mid-1980s through the University of Southern California and the University of California, Los Angeles.

It was not feasible to apply this theory to this study given the unique occurrences of property and violent crimes, the design of neighborhoods throughout each city, and the economic profile of the cities – which no longer aligned with a concentric theory model.

2.3.4 Rational Choice Perspective

Rational Choice Perspective, developed in the United Kingdom, focuses mainly upon the offender's decision-making process. Its main assumption is that offending is purposive behavior, designed to benefit the offender in some way (Felson and Clarke 1998). In basic terms, offenders are thought to consider the immediate characteristics of possible targets in light of the perceived situational conditions surrounding the targets. These conditions include the likely risks, efforts and potential rewards associated with committing the crime in that particular place and time based upon prior experience tempered by their current motivation. Testing this explanation generally involves surveys and interviews with offenders to get a sense of the rationale that led them to offend in the first place. It also uses interviews with repeat offenders to analyze the psychology behind their recidivism.

Two fundamental assumptions must be met if this information is to meet the validity threshold for research. First, the offenders identified and interviewed must be able to articulate what place attributes they considered when deciding on a specific target. Second, a large enough sample group of offenders must be identified to develop credible results. As interviews with active offenders were not within the scope of this study, it was implausible to use this perspective to account for observed crime patterns in the study areas.

2.3.5 Routine Activity Theory

In 1979, Cohen and Felson presented an approach to analyzing crime, which they called the “routine activity approach.” They argued that “structural changes in routine activity patterns can influence crime rates by affecting the convergence in space and time of...three minimal elements of direct-contact predatory violations: (1) motivated offenders, (2) suitable targets, and (3) the absence of capable guardians against a violation” (Felson and Clarke 1998, 589). It is currently one of the more widely used theories.

During the 1960s and 1970s burglary rates and patterns changed dramatically, leading Felson to argue that social disorganization was not a likely explanation for variations in property crime. Alternatively, he reasoned that, widespread changes in routine behavior, in this case the influx of women into the paid workforce and away from home during the day, offered a better explanation for higher rates of burglary (Felson and Clarke 1998). It is yet to be determined whether this continues to be a plausible rationale, given the broad changes in employment patterns that occurred in all study areas from 2006 to 2008. Unemployment was considerably higher than in previous years for the city of Atlanta. According to the theory, this would have decreased some property crimes, as it could be presumed that more people were at home providing a greater guardianship in the respective neighborhoods. The cities of Seattle and Chicago are examined for consistency with Atlanta. Regardless, Routine Activity Theory has value and is used for this study.

2.3.6 The GIS School and Environmental Criminology

Environmental Criminology has become one of the leading theoretical approaches to the study of criminal offenses, employing some aspects of geographic principles. This theoretical approach often goes together with The GIS School as it relies on the use of a geographic information system to analyze and visualize research. Environmental criminology is defined as, "the study of crime, criminality, and victimization as they relate, first, to particular places, and secondly, to the way that individuals and organizations shape their activities spatially, and in so doing are in turn influenced by place-based or spatial factors" (Bottoms and Wiles, 2001, 620). Environmental criminology became more widely known when Patricia and Paul Brantingham published their work in the discipline (1981). Within that text, they outlined the principles of "crime pattern theory."

A more concise overview of this discipline can be found in the work of Bottoms and Wiles (2001). They carefully explained the concept of environmental criminology in sections, managing to stay clear of overburdening formulas, and choosing instead to focus on practical examples. One such study was completed by Per-Olof Wikström (1991) which illustrated the geographic distribution of selected police-recorded offenses in Stockholm, Sweden. In keeping with earlier work by Bottoms and Baldwin (1976), Wikström was able to show that offenses tended to be clustered around the city center. What later studies revealed was that crime patterns could be drastically altered by changing the environment, or in the case of one particular study from Wiles and Costello (2006), adding the development of a large shopping mall, which reduced crime by 14 percent.

2.3.7 Crime Pattern Theory

Crime Pattern Theory asserts that crime concentrations reflect the aggregate patterning of individual activity preferences shaped by social networks, economic forces, and political and legal influences. It is the reason “crimes do not occur randomly or uniformly in time or space or society” (Brantingham and Brantingham 2008, 79). The term “pattern” in this context was used “to describe recognizable inter-connectiveness of objects, rules and processes” (Brantingham and Brantingham 2008, 79). Crime pattern theory also asserts that patterns can be detected “only through an initial insight...that is embedded within the environment as a whole” (2008, 79). Meaning, some patterns of crime events are obvious while others are not. Detection of patterns that are less obvious require a more complex set of analyses.

Not only does crime pattern theory look at individual patterns, it establishes heuristics that outline the probability of interaction between an offender and his/her target within the same space and time. For example, Wikström (1991) illustrated the geographic distribution of selected police-recorded offenses in Stockholm, Sweden. In keeping with earlier work by Bottoms and Baldwin (1976), Wikström was able to show that offenses tended to be clustered around the city center. What later studies revealed was that crime patterns could be drastically altered by changing the environment, or in the case of one particular study (Wiles and Costello 2006), adding the development of a large shopping mall, which reduced crime by 14 percent. This means land use, roads, and the socio-economic status of residents and workers (2002) need to be considered when analyzing criminal activity.

2.3.8 Crime Attractors

Though not a theory, per se, the science of discovering what attracts crime to certain locations while other places appear to remain virtually unaffected by criminal activity has continued to challenge researchers. It seems obvious to conclude that concentrated areas of poverty, single parent households and an overall degradation of a neighborhood attract crime. However, there are other elements identified by Brantingham and Brantingham (1995) that include land uses, particularly the creation of roadway corridors for criminals to travel in anonymity, meaning alley ways and service roads that are not normally used for regular movement throughout the city.

Physical and perceptual edges of locations attract crime (Brantingham and Brantingham 1995). These include places like parking lots, areas surrounding large sporting events, and even territorial boundaries, such as the division between a neighborhood of affluence and one that is not. This could be the perception of affluence, such as that of a gated community. For example, Magnolia Park, a mixed-income community in Atlanta, Georgia, experienced higher residential burglary rates than the surrounding homes in 2008 (English 2011). The community is located within in the municipal boundaries of Vine City, which borders the Georgia Dome. Across the street from the gated community is a Walmart

Superstore – a place that attracts people from areas outside of the immediate community, including criminals looking for targets. While the Walmart might be considered a "crime generator", a place that creates opportunities for criminals, the area as a whole would be closer to a blend of the two – an attractor and a generator (Brantingham and Brantingham 1995).

As this research involves the study of micro-level events that include geographic, temporal and attribute patterns across the data, as well as discovery of hidden attractors, Crime Pattern Theory was the most appropriate choice for the theoretical approach of this study. Routine Activity Theory can be combined with Crime Pattern Theory for a more thorough criminological exploration of the phenomena occurring in each study area; however, at no time were offenders interviewed for this study. The research is solely based upon the analyses of secondary data acquired without offender interaction.

2.4 Clustering Methods

It has been noted by Griffiths and Chavez (2014) that the role of space and place has enjoyed a long tradition in the domain of American criminology. It began with the research of Shaw and McKay (1942). Advances in the analysis of crime and discovery of crime patterns within the domain of Geography have occurred quite slowly and sporadically over the years. While having a geographic information system (GIS) to analyze point data made the mapping of incidents more efficient, it did not necessarily mean what was being spatially analyzed equated to scientific discovery. Moreover, as clustering methods became more prevalent in the subfield of crime analysis, there seemed to be a greater focus on "hotspot" policing, whereby law enforcement agencies would police according to where the high-density clusters were located. Once the density waned, the agency would move to the next problem area. This method of policing has been referred to as "cluster busting." The method is reasonably effective; however, in many cases the success is temporary, suggesting that the problem may be more deep-rooted than agencies initially perceived.

The identification of hotspots should be the first step for a policing or crime reduction agency to take for determining where to deploy resources (Chainey et al. 2008). This can be done using point density mapping, grid thematic mapping, or kernel density estimation, as well as other cluster identifying techniques. These methods are familiar to several domains within the social and natural sciences, including geography and criminology.

2.5 Longitudinal Analysis

The study of crime from a longitudinal perspective has varied in the literature. Much of the available research on the analysis of discrete data over an extended period is within the health domain in the field of disease analysis. Greenberg (2010) highlights some reasons why the approach to longitudinal studies in criminology have changed over the years. The most poignant was that there are longer spans of time periods available with data, especially aggregated datasets (Greenberg 2010). Furthermore, there are better statistical tools available for researching these much larger datasets.

Given Greenberg's insights, it has only been within the past decade or so that substantial analyses of reported crime events have been examined at the micro level in geographic longitudinal studies (Brower and Carroll 2007; Groff et al. 2010; Braga et al. 2011). There has been an even greater focus on street segments as attractors and/or generators of criminal activity (Weisburd, et al. 2004; Groff et al. 2010; Curman et al.

2015; Haberman and Ratcliffe 2015) as researchers work toward a better understanding of how and why crime clusters exist in certain locations. The Groff work specifically asked whether examination of crime trends was necessary, using a longitudinal approach to the study. While the study explored 16 years of data in the Seattle, Washington area, it and other studies (Weisburd et al. 2004, 2009, Curman et al. 2015; Haberman and Ratcliffe 2015) focused mainly on the location or 'the where' of crime events. Understanding where crime occurs is important; however, addressing the 'why' beyond obvious factors (e.g. gang activity, open drug markets, bus stops) remains inadequately addressed in the geography or the criminology domain, especially when analyzing long-term, high-crime areas.

Attempting to identify causation is wrought with many pitfalls. As outlined by Montello and Sutton, "correlation is causality, but the specific pattern of that causality is ambiguous" (143). Discovering attributes that are highly correlated with crime events can be accomplished, and this study will make such effort. However, while the correlations of crime predictors may infer some level of causality, identifying the pattern thereof carries an equal, if not greater, level of uncertainty. Additionally, missing data within the datasets could add to the uncertainty of the inferences. The problem is well known in the fields of public health, medicine, and the social sciences, yet the "appropriate handling of missing data in longitudinal studies remains [statistically vexing]" (Daniels and Hogan 2008). I believe, though, that due to the nature of reported crime data and the volume of available data, it is still possible to conduct a geographic study whereby calculations using crime datasets with missing entries may still produce robust and informative outcomes.

2.6 Strategic Analysis

The term “strategic analysis” for the purposes of this study is used to define the process of longitudinal analysis. Such analyses are often referred to by law enforcement as “administrative analysis.” Roth et al. (2013), in a survey of Northeastern law enforcement agencies, indicated that strategic analysis was an unmet need. “All participating law enforcement agencies emphasized that it only is through such long-term, strategic spatiotemporal analysis of criminal activity that institutionalized criminal activity may be mitigated and blighted communities may be revitalized” (Roth et al. 2013, 239). However, longitudinal analyses have generally been by the numbers, aggregating to a larger administrative policing area. This study is designed in part to address that unmet need by providing methods for analysts to conduct the type of strategic analysis being requested.

2.7 Geographic Mapping Methods and Crime Analysis

The analysis and geographic mapping of crime events has advanced well beyond simple pin maps. Mapping now incorporates computational methods for density discovery. However, cartographically, visual representations of crime have not advanced as far – if at all. Most geographic mapping of crime remains within two-dimensional space.

Within the field of policing, it has become common practice to visualize crime events to understand locations and times of clustered phenomena. While current cluster mapping techniques (i.e., hot-spot mapping and kernel density estimation) have been well utilized in policing, these methods when used in isolation are limited in their approach to revealing hidden attractors of crime across time and space in a specific location. Though there are several known attractors of crime, like drug markets, and bus stops (Block and Block 1995; Brantingham and Brantingham 1995; Weisburd and Green 1995; Hart and

Miethe 2014), as well as land use concentrations (e.g., bars, motels and public housing), finding relevant relationships beyond the obvious will require a different mapping approach.

Analyzing multivariate attribute space over time and creating meaningful visualizations can be challenging. On the one hand, there is more than a single spatial attribute (i.e., coffee shop locations or burglary locations), and on the other hand, there are multidimensional temporal attributes (i.e., time of day, day of week, year). Converging all of those elements into a two-dimensional map space and have it make sense is complicated, especially when considering the more popular mapping visualization techniques used in crime analysis, like choropleth, hotspot, and kernel density mapping. While those styles of mapping can accommodate visualizing a small number of attributes quite well, adding a dynamic time component generally means creating co-maps, whereby each map is its own specific unit of time. The anticipated outcome of using a co-mapping method to visualize the data is that it provides a practical way to understand the analysis and results being presented.

A gap in the current research is the ability to determine what combinations of attributes are attracting crime to a location for an extended period. While there have been recent studies focusing on crime concentration at street segments (Weisburd, et al. 2012; Hart and Miethe 2014; Curman, et al. 2015), the majority of the studies have primarily examined obvious crime attractors like bars, transit stops, automated teller machines (ATM), fast food establishments, etc. The studies are useful, in that they examine where crime concentrates at a micro-level of analysis. However, the question of persistent crime clusters spanning several years continues to lack of a much deeper study of the attributes attracting crime to the locations where there is a high, sustained level of concentration.

Chapter 3. Data and Study Areas

3.1 Data

Data were collected from several sources. These data included quantitative and qualitative sources for crime, business, socio-economic, services, housing authority, census enumerations, transportation and economic activity. The data contain both spatial and temporal elements, therefore collating the sources required some attribute matching and will be addressed later in the methodology section.

3.1.1 Crime Data

Disaggregated, street-level reported crime data was gathered from the jurisdictions of Atlanta (Table 1a), Seattle (Table 1b) and Chicago Police Departments (Table 1c) for the years 2004 through 2013 (2008 to 2013 for Seattle). These data are address-level incidents (where available), which allow for greater flexibility when aggregating for analyses.

Table 1a. Sample of Atlanta raw crime data (partial view)

ID	ADDRESS	INCIDENT#	UCR#	OFFENCE	ZONE	BEAT	LOC	RPT_DT	DT_FM	DAY_FM	TM_FM	DT_TO	DAY_TO	TM_TO	SHIFT	ST#	ST_NAM	TYPE	QUAD	APT	I-SECT	WEAPON	DISPO	#VICS	X	Y	NEIGHBOURHOOD
1	799 MORELAND AVE SE	040010728	0690	LAR-OTHR-FREE TEXT	6	609	26	2004-01-01	2004-01-01	Thu	7:20:00 AM	2004-01-01	Thu	8:00:00 AM	Day	799	MORELAND	AVE	SE			0035		0	-84.34943	33.73265	Ormewood Park
2	2043 MARTIN L KING JR DR NW	040010729	0532	ATTEMPT BURG-FORC ENTRY-NONRES	4	402	12	2004-01-01	2003-12-01	Mon	11:00:00 PM	2004-01-01	Thu	7:10:00 AM	Unk	2043	MARTIN L KING JR	DR	NW			0023		0	-84.45371	33.75005	
3	2148 HILLS AVE NW	040010739	0512	BURG-FORCD ENTRY-NONRESID	2	208	24	2004-01-01	2004-01-01	Thu	7:30:00 AM	2004-01-01	Thu	7:40:00 AM	Day	2148	HILLS	AVE	NW	I		0014		0	-84.43069	33.81445	Underwood Hills
4	416 GARTRELL ST SE	040010766	0511	BURGLARY-FORCED ENTRY-RESIDENC	5	510	20	2004-01-01	2003-12-31	Wed	9:00:00 PM	2004-01-01	Thu	8:30:00 AM	Morn	416	GARTRELL	ST	SE			0099		0	-84.37382	33.75299	Sweet Auburn
5	356 BOULEVARD NE	040010768	0720	THEFT OF TRUCK/VAN/BUS	5	510	23	2004-01-01	2004-01-01	Thu	7:30:00 AM	2004-01-01	Thu	7:40:00 AM	Day	356	BOULEVARD		NE			0035		0	-84.37207	33.76422	Old Fourth Ward
6	1063 WESTSHIRE PL NW	040010775	0710	AUTOTHEFT	5	501	18	2004-01-01	2003-12-31	Wed	5:30:00 PM	2004-01-01	Thu	8:30:00 AM	Morn	1063	WESTSHIRE	PL	NW			0006		0	-84.39655	33.78371	Home Park
7	1150 CRESCENT AVE NE	040010788	0670	LARCENY-FROM BUILDING	5	502	03	2004-01-01	2004-01-01	Thu	1:00:00 AM	2004-01-01	Thu	2:30:00 AM	Morn	1150	CRESCENT	AVE	NE			0099		0	-84.38437	33.78601	Midtown
8	84 12TH ST NE	040010789	0670	LARCENY-FROM BUILDING	5	502	03	2004-01-01	2003-12-31	Wed	10:30:00 PM	2003-12-31	Wed	11:30:00 PM	Morn	84	12TH	ST	NE			0099		0	-84.38493	33.78463	Midtown
9	577 STOKESWOOD AVE SE	040010794	0511	BURGLARY-FORCED ENTRY-RESIDENC	6	610	20	2004-01-01	2003-12-31	Wed	11:00:00 PM	2004-01-01	Thu	8:40:00 AM	Morn	577	STOKESWOOD	AVE	SE			0099		0	-84.34483	33.73919	East Atlanta
10	52 FAIRBURN RD NW	040010799	0650	LAR-PARTS FROM VEHICLE	4	413	18	2004-01-01	2003-12-31	Wed	10:20:00 PM	2004-01-01	Thu	12:30:00 AM	Morn	52	FAIRBURN	RD	NW			0099		0	-84.50518	33.76038	Adamsville
11	188 14TH ST NE	040010800	0670	LARCENY-FROM BUILDING	5	504	14	2004-01-01	2003-12-25	Thu	11:30:00 PM	2004-01-01	Thu	8:00:00 AM	Unk	188	14TH	ST	NE	2302		0099		0	-84.38164	33.78658	Midtown
12	836 DIXIE AVE NE	040010850	0650	LAR-PARTS FROM VEHICLE	6	604	13	2004-01-01	2003-12-31	Wed	10:30:00 PM	2004-01-01	Thu	7:00:00 AM	Morn	836	DIXIE	AVE	NE			0099		0	-84.36053	33.75687	Inman Park
13	760 SIDNEY MARCUS BLVD NE	040010867	0670	LARCENY-FROM BUILDING	2	204	26	2004-01-01	2003-12-31	Wed	4:00:00 PM	2003-12-31	Wed	7:00:00 PM	Eve	760	SIDNEY MARCUS	BLVD	NE	325		0099		0	-84.36406	33.82592	Lindbergh/Morosgo
14	1202 WEST MARIETTA ST NW	040010868	0670	LARCENY-FROM BUILDING	1	102	04	2004-01-01	2003-12-31	Wed	11:56:00 PM	2004-01-01	Thu	12:01:00 AM	Morn	1202	WEST MARIETTA	ST	NW			0099		0	-84.42664	33.78599	Knight Park/Howell Station
15	306 PONCE DE LEON AVE NE	040010871	0341	ROB-STREET-STRONGARM	5	505	03	2004-01-01	2004-01-01	Thu	9:30:00 AM	2004-01-01	Thu	10:15:00 AM	Day	306	PONCE DE LEON	AVE	NE			0028		0	-84.37709	33.7726	Midtown
16	66 FORSYTH ST SW	040010890	0512	BURG-FORCD ENTRY-NONRESID	5	508	21	2004-01-01	2003-12-31	Wed	4:00:00 PM	2004-01-01	Thu	9:00:00 AM	Unk	66	FORSYTH	ST	SW			0014		0	-84.39337	33.75272	Downtown
17	710 PEACHTREE ST NE	040010897	0670	LARCENY-FROM BUILDING	5	503	20	2004-01-01	2004-01-01	Thu	4:09:00 AM	2004-01-01	Thu	4:09:00 AM	Morn	710	PEACHTREE	ST	NE					0	-84.38483	33.77409	Midtown
18	57 13TH ST NE	040010898	0710	AUTOTHEFT	5	502	18	2004-01-01	2003-12-01	Mon	9:00:00 PM	2004-01-01	Thu	2:15:00 AM	Unk	57	13TH	ST	NE	320		0099		0	-84.38573	33.78555	Midtown
19	795 POLLARD BLVD SW	040010926	0710	AUTOTHEFT	3	302	14	2004-01-01	2004-01-01	Thu	3:00:00 AM	2004-01-01	Thu	10:30:00 AM	Morn	795	POLLARD	BLVD	SW			0099		0	-84.391	33.73324	Summerhill
20	2625 PIEDMONT RD NE	040010933	0630	SHOPLIFTING	2	204	08	2004-01-01	2004-01-01	Thu	11:00:00 AM	2004-01-01	Thu	11:30:00 AM	Day	2625	PIEDMONT	RD	NE			0035	10	0	-84.36699	33.82681	Lindbergh/Morosgo
21	576 GLENWOOD PL SE	040010945	0670	LARCENY-FROM BUILDING	6	609	20	2004-01-01	2003-11-01	Sat	12:00:00 PM	2003-12-24	Wed	12:00:00 PM	Unk	576	GLENWOOD	PL	SE			0099	20	0	-84.35478	33.73841	Ormewood Park
22	1050 TECHWOOD DR NW	040010947	0680	LARCENY-FROM COIN MACHINE	5	501	05	2004-01-01	2003-12-31	Wed	12:00:00 PM	2003-12-31	Wed	5:30:00 PM	Day	1050	TECHWOOD	DR	NW			0099		0	-84.3921	33.78338	Home Park
23	3181 BANKHEAD HWY NW	040010956	0640	LAR-ARTICLES FROM VEHICLE	1	108	18	2004-01-01	2003-12-31	Wed	3:00:00 PM	2004-01-01	Thu	11:00:00 AM	Unk	3181	BANKHEAD	HWY	NW			0035		0	-84.49193	33.78637	Brookview Heights
24	1828 WELLBOURNE DR NE	040010966	0511	BURGLARY-FORCED ENTRY-RESIDENC	6	601	20	2004-01-01	2003-12-31	Wed	8:00:00 AM	2004-01-01	Thu	11:50:00 AM	Unk	1828	WELLBOURNE	DR	NE			0013		0	-84.36019	33.80453	Morningside/Lenox Park
25	516 ELMWOOD RD NW	040010982	0430	AGGR ASLT/BATTERY-OTH WEP	1	105	20	2004-01-01	2004-01-01	Thu	11:30:00 AM	2004-01-01	Thu	11:55:00 AM	Day	516	ELMWOOD	RD	NW			0098		1	-84.43894	33.76924	Grove Park
26	1829 CAMPBELLTON RD SW	040010999	0680	LARCENY-FROM COIN MACHINE	4	406	26	2004-01-01	2003-12-28	Sun	8:00:00 PM	2003-12-29	Mon	4:00:00 PM	Unk	1829	CAMPBELLTON	RD	SW	C-13		0099		0	-84.44856	33.71004	Venetian Hills
27	1986 BAKER RD NW	050011450	0511	BURGLARY-FORCED ENTRY-RESIDENC	1	105	20	2004-01-01	2004-01-01	Thu	5:15:00 PM	2004-01-01	Thu	5:15:00 PM	Eve	1986	BAKER	RD	NW			0033		0	-84.4522	33.77005	Grove Park
28	1986 BAKER RD NW	050011450	0511	BURGLARY-FORCED ENTRY-RESIDENC	1	105	20	2004-01-01	2004-01-01	Thu	5:15:00 PM	2004-01-01	Thu	5:15:00 PM	EVE	1986	BAKER	RD	NW			0033		0	-84.4522	33.77005	Grove Park
29	3414 WELCOME ALL RD SW	033651765	0720	THEFT OF TRUCK/VAN/BUS	4	410	18	2004-01-01	2003-12-31	Wed	8:30:00 PM	2003-12-31	Wed	8:45:00 PM	Eve	3414	WELCOME ALL	RD	SW			0035		0	-84.52219	33.66134	Ben Hill
30	3849 BROWNS MILL RD SE	033651916	0710	AUTOTHEFT	3	309	07	2004-01-01	2003-12-31	Wed	10:20:00 PM	2003-12-31	Wed	10:20:00 PM	Eve	3849	BROWNS MILL	RD	SE			0035		0	-84.39362	33.65279	Glenrose Heights
31	600 MARIETTA ST NW	033651940	0210	RAPE-STRONGARM	5	506		2004-01-01	2004-01-01	Thu	1:00:00 AM	2004-01-01	Thu	1:00:00 AM	Morn	600	MARIETTA	ST	NW					1	-84.39887	33.76951	Downtown
32	737 FRASER ST SE	033652062	0690	LAR-OTHR-FREE TEXT	3	302	20	2004-01-01	2003-12-31	Wed	2:00:00 PM	2003-12-31	Wed	11:00:00 PM	Eve	737	FRASER	ST	SE			0035		0	-84.38647	33.73464	Summerhill
33	553 HIGHLAND AVE NE	033652069	0521	BURG-NO FORCD ENTRY-RESID	5	511		2004-01-01	2003-12-31	Wed	8:00:00 PM	2003-12-31	Wed	11:00:00 PM	Eve	553	HIGHLAND	AVE	NE	15				0	-84.36898	33.76124	Old Fourth Ward
34	637 SIMPSON ST NW	040010090	0640	LAR-ARTICLES FROM VEHICLE	1	111	18	2004-01-01	2003-12-31	Wed	11:00:00 PM	2004-01-01	Thu	12:15:00 AM	Morn	637	SIMPSON	ST	NW			0099		0	-84.40828	33.76351	English Avenue
35	954 HIGHTOWER RD NW	040010100	0341	ROB-STREET-STRONGARM	1	106	26	2004-01-01	2004-01-01	Thu	12:25:00 AM	2004-01-01	Thu	12:35:00 AM	Morn	954	HIGHTOWER	RD	NW			0035	10	0	-84.47444	33.78149	Carey Park
36	3035 MIDDLETON RD NW	040010113	0315	ROB-RESIDENCE-GUN	4	412	26	2004-01-01	2004-01-01	Thu	12:29:00 AM	2004-01-01	Thu	12:29:00 AM	Morn	3035	MIDDLETON	RD	NW	25/93		0001		0	-84.48993	33.75277	
37	615 PEACHTREE ST NE	040010154	0720	THEFT OF TRUCK/VAN/BUS	5	503	18	2004-01-01	2003-12-31	Wed	8:00:00 PM	2004-01-01	Thu	12:30:00 AM	Unk	615	PEACHTREE	ST	NE			0099		0	-84.38487	33.77137	Midtown
38	296 HENRY AARON AVE SW	040010165	0430	AGGR ASLT/BATTERY-OTH WEP	4	411	20	2004-01-01	2004-01-01	Thu	12:35:00 AM	2004-01-01	Thu	12:40:00 AM	Morn	296	HENRY AARON	AVE	SW			0008		1	-84.45709	33.7479	Florida Heights
39	232 FORSYTH ST SW	040010196	0341	ROB-STREET-STRONGARM	5	508		2004-01-01	2003-12-31	Wed	12:01:00 AM	2003-12-31	Wed	12:01:00 AM	Morn	232	FORSYTH	ST	SW					0	-84.39698	33.74807	Downtown
40	2365 CASCADE RD SW	040010260	0511	BURGLARY-FORCED ENTRY-RESIDENC	4	411	26	2004-01-01	2003-12-31	Wed	9:15:00 PM	2004-01-01	Thu	1:00:00 AM	Morn	2365	CASCADE	RD	SW	J-39		0099		0	-84.46638	33.7214	Cascade Heights
41	560 DUTCH VALLEY RD NE	040010278	0430	AGGR ASLT/BATTERY-OTH WEP	6	602	26	2004-01-01	2004-01-01	Thu	1:21:00 AM	2004-01-01	Thu	1:23:00 AM	Morn	560	DUTCH VALLEY	RD	NE	104		0007	10	1	-84.3687	33.79214	Morningside/Lenox Park
42	1051 PEEPLES ST SW	040010321	0420	AGGR ASLT/BATTERY-KNIFE	4	403	13	2004-01-01	2004-01-01	Thu	2:15:00 AM	2004-01-01	Thu	2:15:00 AM	Morn	1051	PEEPLES	ST	SW			0007	10	1	-84.42384	33.72647	Oakland City
43	695 PIEDMONT AVE NE	040010326	0650	LAR-PARTS FROM VEHICLE	5	503	13	2004-01-01	2003-12-31	Wed	10:00:00 PM	2004-01-01	Thu	1:00:00 AM	Morn	695	PIEDMONT	AVE	NE					0	-84.38154	33.77364	Midtown
44	806 MARIETTA ST NW	040010363	0410	AGGR ASLT/BATTERY-GUN	5	501	03	2004-01-01	2004-01-01	Thu	1:57:00 AM	2004-01-01	Thu	2:03:00 AM	Morn	806	MARIETTA	ST	NW			0001		1	-84.40574	33.77401	Marietta Street Artery
45	1232 GREENWICH ST SW	040010373	0511	BURGLARY-FORCED ENTRY-RESIDENC	4	401	20	2004-01-01	2003-12-31	Wed	9:15:00 PM	2004-01-01	Thu	2:00:00 AM	Morn	1232	GREENWICH	ST	SW			0013		0	-84.42799	33.74378	West End
46	1831 HONEYSUCKLE LN SW	040010387	0440	OTH ASLT/BATT OFNS-FR TXT	4	408	26	2004-01-01	2004-01-01	Thu	1:45:00 AM	2004-01-01	Thu	1:50:00 AM	Morn	1831	HONEYSUCKLE	LN	SW	47T		0008	10	1	-84.45336	33.70712	Campbellton Road
47	1068 PEACHTREE ST NE	040010400	0430	AGGR ASLT/BATTERY-OTH WEP	5	502	03	2004-01-01	2004-01-01	Thu	12:40:00 AM	2004-01-01	Thu	1:30:00 AM	Morn	1068	PEACHTREE	ST	NE			0008		1	-84.38358	33.78378	Midtown
48	1642 ALDER CT SE	040010409	0710	AUTOTHEFT	6	608	20	2004-01-01	2004-01-01	Thu	2:15:00 AM	2004-01-01	Thu	2:30:00 AM	Morn	1642	ALDER	CT	SE			0012		0	-84.33686	33.74954	Kirkwood
49	577 RALPH MCGILL BLVD NE	040010422	0512	BURG-FORCD ENTRY-NONRESID	5	511		2004-01-01	2004-01-01	Thu	2:26:00 AM	2004-01-01	Thu	2:35:00 AM	Morn	577	RALPH MCGILL	BLVD	NE					0	-84.36884	33.76386	Old Fourth Ward
50	196 PEACHTREE ST SW	040010596	0720	THEFT OF TRUCK/VAN/BUS	5	508	18	2004-01-01	2004-01-01	Thu	12:01:00 AM	2004-01-01	Thu	2:00:00 AM	Morn	196	PEACHTREE	ST	SW			0001		0	-84.3943	33.74915	Downtown
51	1136 CRESCENT AVE NE	040010601	0670	LARCENY-FROM BUILDING	5	502	03	2004-01-01	2004-01-01	Thu	3:00:00 AM	2004-01-01	Thu	4:00:00 AM	Morn	1136	CRESCENT	AVE	NE			0098		0	-84.38434	33.78579	Midtown
52	85 JOHN WESLEY DOBBS AVE NE	040010610	0720	ATTEMPTED THEFT TRUCK/VAN/BUS	5	509	18	2004-01-01	2003-12-31	Wed	4:00:00 PM	2004-01-01	Thu	3:00:00 AM	Eve	85	JOHN WESLEY DOBBS	AVE	NE			0099		0	-84.38499	33.75701	Downtown
53	2788 FORREST HILLS DR SW	040010628	0317	ROB-MISC-GUN	3	309	14	2004-01-01	2003-12-31	Wed	10:00:00 PM	2004-01-01	Thu	4:00:00 AM	Morn	2788	FORREST HILLS	DR	SW			0001		0	-84.39925	33.67775	Hammond Park

Table 1b. Sample of Seattle raw crime data

Report_Num	Offense_ID	Offense_St	Offense_En	Report_Dat	Group_A_B	Crime_Agai	Offense_Pa	Offense	Offense_Co	Precinct	Sector	Beat	MCPP	100_Block	Longitude	Latitude
2008-000048	7664187159.0000000000	12/31/2007		1/1/2008	A	PROPERTY	ROBBERY	Robbery	120	N	U	U1	UNIVERSITY	NE 50TH ST / 19TH AVE NE	-122.30719104100	47.66486034000
2008-000095	7647383752.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	W	Q	Q3	QUEEN ANNE	7XX BLOCK OF 5TH AVE N	-122.34756103400	47.62585212000
2008-000123	7670757380.0000000000	12/31/2007	12/31/2007	1/1/2008	A	PROPERTY	MOTOR VEHICLE THEFT	Motor Vehicle Theft	240	S	R	R3	HILLMAN CITY	59XX BLOCK OF 37TH AVE S	-122.28626451800	47.54889699000
2008-000136	7688363525.0000000000	1/1/2008		1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	W	Q	Q3	QUEEN ANNE	3XX BLOCK OF 5TH AVE N	-122.34759442300	47.62175679000
2008-000142	7651305802.0000000000	1/1/2008		1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	W	D	D2	SLU/CASCADE	23XX BLOCK OF 4TH AVE	-122.34458490200	47.61575309000
2008-000154	7656639687.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	S	R	R3	COLUMBIA CITY	50XX BLOCK OF 37TH AVE S	-122.28614915200	47.55626345000
2008-000193	7647504502.0000000000	1/1/2008		1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	S	S	S2	BRIGHTON/DUNLAP	48XX BLOCK OF S HOLDEN ST	-122.27131489600	47.53366162000
2008-000335	7647947388.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	E	E	E2	CAPITOL HILL	E UNION ST / BOYLSTON AVE	-122.32344008900	47.61298674000
2008-000345	7644695807.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	BURGLARY/BREAKING&ENTERING	Burglary/Breaking & Entering	220	SW	F	F1	PIGEON POINT	38XX BLOCK OF 22ND AVE SW	-122.36115842800	47.56925498000
2008-000347	7631898480.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	E	E	E3	FIRST HILL	TERRY AVE / CHERRY ST	-122.32429358400	47.60673262000
2008-000392	7700636913.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	ROBBERY	Robbery	120	N	U	U1	UNIVERSITY	56XX BLOCK OF BROOKLYN AVE NE	-122.31416560000	47.67034534000
2008-000423	7669511591.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	BURGLARY/BREAKING&ENTERING	Burglary/Breaking & Entering	220	W	K	K1	DOWNTOWN COMMERCIAL	1XX BLOCK OF CHERRY ST	-122.33372665800	47.60278737000
2008-000435	7698287390.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	W	M	M2	SLU/CASCADE	VIRGINIA ST / 3RD AVE	-122.34089245400	47.61239802000
2008-000450	7692761123.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	E	E	E1	CAPITOL HILL	17XX BLOCK OF SUMMIT AVE	-122.32555228800	47.61704061000
2008-000470	7645277189.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	BURGLARY/BREAKING&ENTERING	Burglary/Breaking & Entering	220	N	N	N2	NORTHGATE	115XX BLOCK OF CORLISS AVE N	-122.33139622600	47.71270937000
2008-000476	7669711437.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	MOTOR VEHICLE THEFT	Motor Vehicle Theft	240	N	U	U1	UNIVERSITY	50XX BLOCK OF 11TH AVE NE	-122.31632469000	47.66568421000
2008-000484	7699686578.0000000000	1/1/2008		1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	W	M	M3	DOWNTOWN COMMERCIAL	14XX BLOCK OF 3RD AVE	-122.33733875000	47.60925299000
2008-000485	7683699386.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	N	B	B2	FREMONT	49XX BLOCK OF DAYTON AVE N	-122.35271388700	47.66466105000
2008-000489	7626667426.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	MOTOR VEHICLE THEFT	Motor Vehicle Theft	240	N	N	N2	NORTHGATE	143XX BLOCK OF WALLINGFORD AVE N	-122.33697198500	47.73322354000
2008-000499	7699117404.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	S	S	S2	BRIGHTON/DUNLAP	44XX BLOCK OF S KENYON ST	-122.27761090300	47.53154603000
2008-000505	7633136158.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	N	B	B3	WALLINGFORD	55XX BLOCK OF CANFIELD PL N	-122.33589959900	47.66958912000
2008-000518	7676934711.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	N	B	B3	WALLINGFORD	55XX BLOCK OF KENWOOD PL N	-122.33486964600	47.66980721000
2008-000525	7641187579.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	BURGLARY/BREAKING&ENTERING	Burglary/Breaking & Entering	220	N	N	N1	BITTERLAKE	7XX BLOCK OF NW 116TH ST	-122.36619956800	47.71301071000
2008-000525	7641187576.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	MOTOR VEHICLE THEFT	Motor Vehicle Theft	240	N	N	N1	BITTERLAKE	7XX BLOCK OF NW 116TH ST	-122.36619956800	47.71301071000
2008-000531	7625848353.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	E	E	E1	CAPITOL HILL	2XX BLOCK OF BROADWAY E	-122.32088228600	47.62049180000
2008-000537	7671920542.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	N	J	J2	BALLARD NORTH	77XX BLOCK OF JONES AVE NW	-122.38646824400	47.68589564000
2008-000551	7635336133.0000000000	12/28/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	S	R	R1	NORTH BEACON HILL	19XX BLOCK OF 15TH AVE S	-122.31336661400	47.58594718000
2008-000570	7626098202.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	MOTOR VEHICLE THEFT	Motor Vehicle Theft	240	S	R	R3	HILLMAN CITY	42XX BLOCK OF S KENNY ST	-122.27946811300	47.54894101000
2008-000581	7642812387.0000000000	12/31/2007	12/31/2007	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	W	Q	Q3	SLU/CASCADE	4XX BLOCK OF 5TH AVE N	-122.34758720100	47.62265884000
2008-000606	7655448349.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	N	B	B2	FREMONT	36XX BLOCK OF DAYTON AVE N	-122.35235312500	47.65295358000
2008-000612	7634410886.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	E	G	G1	FIRST HILL	3XX BLOCK OF 9TH AVE	-122.32344394000	47.60412808000
2008-000622	7655777276.0000000000	12/24/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	W	Q	Q2	QUEEN ANNE	10XX BLOCK OF W EMERSON ST	-122.37117265100	47.65338037000
2008-000639	7630241596.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	MOTOR VEHICLE THEFT	Motor Vehicle Theft	240	S	R	R3	COLUMBIA CITY	M L KING JR WAY S / S ALASKA ST	-122.29351189200	47.56082144000
2008-000640	7627376012.0000000000	12/28/2007	1/1/2008	1/1/2008	A	PROPERTY	BURGLARY/BREAKING&ENTERING	Burglary/Breaking & Entering	220	E	G	G3	MADRONA/LESCHI	4XX BLOCK OF 25TH AVE S	-122.29990096900	47.59868287000
2008-000642	7700199643.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	BURGLARY/BREAKING&ENTERING	Burglary/Breaking & Entering	220	S	R	R1	MID BEACON HILL	49XX BLOCK OF BEACON AVE S	-122.30347034600	47.55670813000
2008-000673	7678418071.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	MOTOR VEHICLE THEFT	Motor Vehicle Theft	240	N	B	B3	WALLINGFORD	35XX BLOCK OF WALLINGFORD AVE N	-122.33633091500	47.64984861000
2008-000686	7639976650.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	MOTOR VEHICLE THEFT	Motor Vehicle Theft	240	W	D	D3	EASTLAKE - WEST	22XX BLOCK OF EASTLAKE AVE E	-122.32589341500	47.63898704000
2008-000692	7700284887.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	E	G	G3	MADRONA/LESCHI	2XX BLOCK OF 28TH AVE S	-122.29585380100	47.60057085000
2008-000700	7699103321.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	S	R	R1	NORTH BEACON HILL	13XX BLOCK OF 15TH AVE S	-122.31422133300	47.59147341000
2008-000712	7685042083.0000000000	12/27/2007	1/1/2008	1/1/2008	A	PROPERTY	BURGLARY/BREAKING&ENTERING	Burglary/Breaking & Entering	220	N	N	N1	BITTERLAKE	143XX BLOCK OF PHINNEY AVE N	-122.35425663300	47.73320154000
2008-000763	7692949991.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	E	G	G2	CENTRAL AREA/SQUIRE PARK	5XX BLOCK OF 17TH AVE	-122.31024879600	47.60622905000
2008-000768	7653190807.0000000000	12/31/2007	1/1/2008	1/23/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	N	B	B2	FREMONT	N 47TH ST / LINDEN AVE N	-122.34857767700	47.66287307000
2008-000801	7646145558.0000000000	12/31/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	W	D	D3	EASTLAKE - WEST	15XX BLOCK OF FRANKLIN AVE E	-122.32472345000	47.63305738000
2008-000809	7627947758.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PERSON	ASSAULT OFFENSES	Aggravated Assault	13A	E	G	G2	JUDKINS PARK/NORTH BEACON HILL	E YESLER WAY / 22ND AVE	-122.30373893900	47.60166928000
2008-000843	7690855935.0000000000	12/21/2007	12/28/2007	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	N	J	J2	BALLARD NORTH	28XX BLOCK OF NW 75TH ST	-122.39369288700	47.68309201000
2008-000859	7678963592.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	W	Q	Q3	SLU/CASCADE	BROAD ST / TAYLOR AV N	-122.34629152500	47.62173083000
2008-000898	7675699594.0000000000	12/3/2007	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	W	Q	Q3	QUEEN ANNE	4XX BLOCK OF QUEEN ANNE AVE N	-122.35672457000	47.62269258000
2008-000997	7626539042.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	LARCENY-THEFT	Theft From Motor Vehicle	23F	N	N	N2	NORTHGATE	116XX BLOCK OF AURORA AVE N	-122.34483426800	47.71354798000
2008-001003	7646547172.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	ROBBERY	Robbery	120	N	J	J3	ROOSEVELT/RAVENNA	CHAPIN PL N / N 65TH ST	-122.33020211400	47.67595671000
2008-001029	7693830674.0000000000	1/1/2008	1/1/2008	1/1/2008	A	PROPERTY	BURGLARY/BREAKING&ENTERING	Burglary/Breaking & Entering	220	W	Q	Q3	QUEEN ANNE	2XX BLOCK OF QUEEN ANNE AVE N	-122.35674262200	47.62035713000

Table 1c. Sample of Chicago raw crime data

Case Number	Date	Block	IUCR	Primary Type	Description	Location Description	Arrest	Domestic	Beat	District	Ward	Community Area	FBI Code	X Coordinate	Y Coordinate	Year	Updated On	Latitude	Longitude	Location
HK720643	10/30/2004 14:45	003XX E 138TH ST	610	BURGLARY	FORCIBLE ENTRY	RESIDENCE	FALSE	FALSE	533	5	9	54	5	1181006	1813909	2004	4/15/2016 8:55	41.644608	-87.613461	(41.644607523, -87.613461244)
HK409180	6/4/2004 15:45	003XX E 138TH ST	820	THEFT	$500 AND UNDER	FACTORY/MANUFACTURING BUILDING	FALSE	FALSE	533	5	9	54	6	1181117	1813910	2004	4/15/2016 8:55	41.644608	-87.613055	(41.644607723, -87.613055128)
HK624657	9/15/2004 6:15	003XX E 138TH ST	1320	CRIMINAL DAMAGE	TO VEHICLE	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	533	5	9	54	14	1181117	1813910	2004	4/15/2016 8:55	41.644608	-87.613055	(41.644607723, -87.613055128)
HK624656	9/15/2004 3:30	003XX E 138TH ST	1320	CRIMINAL DAMAGE	TO VEHICLE	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	533	5	9	54	14	1181117	1813910	2004	4/15/2016 8:55	41.644608	-87.613055	(41.644607723, -87.613055128)
HK624655	9/15/2004 4:00	003XX E 138TH ST	820	THEFT	$500 AND UNDER	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	533	5	9	54	6	1181117	1813910	2004	4/15/2016 8:55	41.644608	-87.613055	(41.644607723, -87.613055128)
HK644121	9/24/2004 4:00	003XX E 138TH ST	810	THEFT	OVER $500	VEHICLE NON-COMMERCIAL	FALSE	FALSE	533	5	9	54	6	1181117	1813910	2004	4/15/2016 8:55	41.644608	-87.613055	(41.644607723, -87.613055128)
HK405165	6/2/2004 19:14	005XX E 138TH ST	5002	OTHER OFFENSE	OTHER VEHICLE OFFENSE	STREET	FALSE	FALSE	533	5	9	54	26	1182191	1813919	2004	4/15/2016 8:55	41.644608	-87.609126	(41.644607732, -87.609125704)
HK587741	8/28/2004 16:30	003XX E 138TH ST	810	THEFT	OVER $500	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	533	5	9	54	6	1180950	1813909	2004	4/15/2016 8:55	41.644609	-87.613666	(41.644608806, -87.613666116)
HK470778	7/3/2004 2:40	003XX E 138TH ST	454	BATTERY	AGG PO HANDS NO/MIN INJURY	STREET	TRUE	FALSE	533	5	9	54	08B	1181028	1813910	2004	4/15/2016 8:55	41.64461	-87.613381	(41.644609763, -87.613380728)
HK325956	4/24/2004 20:15	012XX E 138TH ST	820	THEFT	$500 AND UNDER	COMMERCIAL / BUSINESS OFFICE	FALSE	FALSE	533	5	9	54	6	1186873	1813969	2004	4/15/2016 8:55	41.644636	-87.591995	(41.644635743, -87.59199544)
HK534557	8/3/2004 16:00	012XX E 138TH ST	486	BATTERY	DOMESTIC BATTERY SIMPLE	OTHER	FALSE	TRUE	533	5	9	54	08B	1186873	1813969	2004	4/15/2016 8:55	41.644636	-87.591995	(41.644635743, -87.59199544)
HK516856	7/26/2004 9:00	137XX S BRAINARD AVE	820	THEFT	$500 AND UNDER	STREET	FALSE	FALSE	433	4	10	55	6	1200634	1814280	2004	4/15/2016 8:55	41.645153	-87.541642	(41.645153444, -87.541642025)
HK233739	3/11/2004 14:00	137XX S LEYDEN AVE	1310	CRIMINAL DAMAGE	TO PROPERTY	RESIDENCE	FALSE	FALSE	533	5	9	54	14	1180531	1814120	2004	4/15/2016 8:55	41.645197	-87.615193	(41.645197412, -87.615192567)
HK612004	9/8/2004 23:00	137XX S LEYDEN AVE	1310	CRIMINAL DAMAGE	TO PROPERTY	RESIDENTIAL YARD (FRONT/BACK)	FALSE	FALSE	533	5	9	54	14	1180531	1814120	2004	4/15/2016 8:55	41.645197	-87.615193	(41.645197412, -87.615192567)
HK102638	1/2/2004 12:30	137XX S AVENUE O	2825	OTHER OFFENSE	HARASSMENT BY TELEPHONE	RESTAURANT	FALSE	TRUE	433	4	10	55	26	1201079	1814333	2004	4/15/2016 8:55	41.645288	-87.540012	(41.645287658, -87.540012254)
HK118713	1/11/2004 7:36	137XX S AVENUE O	486	BATTERY	DOMESTIC BATTERY SIMPLE	STREET	FALSE	TRUE	433	4	10	55	08B	1201079	1814333	2004	4/15/2016 8:55	41.645288	-87.540012	(41.645287658, -87.540012254)
HK189470	2/18/2004 8:45	137XX S AVENUE O	033A	ROBBERY	ATTEMPT: ARMED-HANDGUN	RESTAURANT	TRUE	FALSE	433	4	10	55	3	1201079	1814333	2004	4/15/2016 8:55	41.645288	-87.540012	(41.645287658, -87.540012254)
HK206537	2/26/2004 20:10	137XX S AVENUE O	312	ROBBERY	ARMED:KNIFE/CUTTING INSTRUMENT	OTHER COMMERCIAL TRANSPORTATION	FALSE	FALSE	433	4	10	55	3	1201079	1814333	2004	4/15/2016 8:55	41.645288	-87.540012	(41.645287658, -87.540012254)
HK811279	12/16/2004 1:36	137XX S AVENUE O	031A	ROBBERY	ARMED: HANDGUN	RESTAURANT	FALSE	FALSE	433	4	10	55	3	1201079	1814333	2004	4/15/2016 8:55	41.645288	-87.540012	(41.645287658, -87.540012254)
HK824990	12/23/2004 16:25	137XX S AVENUE O	820	THEFT	$500 AND UNDER	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	6	1201073	1814399	2004	4/15/2016 8:55	41.645469	-87.540032	(41.645468921, -87.540031983)
HK231957	3/10/2004 9:00	137XX S AVENUE O	820	THEFT	$500 AND UNDER	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	6	1201071	1814451	2004	4/15/2016 8:55	41.645612	-87.540038	(41.645611665, -87.540037549)
HK798628	12/8/2004 18:30	137XX S AVENUE O	1320	CRIMINAL DAMAGE	TO VEHICLE	OTHER	FALSE	FALSE	433	4	10	55	14	1201071	1814458	2004	4/15/2016 8:55	41.645631	-87.540037	(41.645630874, -87.540037314)
HK805881	12/12/2004 10:00	137XX S AVENUE O	810	THEFT	OVER $500	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	6	1201071	1814458	2004	4/15/2016 8:55	41.645631	-87.540037	(41.645630874, -87.540037314)
HK829805	12/22/2004 17:00	137XX S AVENUE O	810	THEFT	OVER $500	OTHER	FALSE	FALSE	433	4	10	55	6	1201071	1814458	2004	4/15/2016 8:55	41.645631	-87.540037	(41.645630874, -87.540037314)
HK798578	12/9/2004 8:04	137XX S AVENUE O	850	THEFT	ATTEMPT THEFT	OTHER	FALSE	FALSE	433	4	10	55	6	1201071	1814458	2004	4/15/2016 8:55	41.645631	-87.540037	(41.645630874, -87.540037314)
HK831290	12/27/2004 22:20	137XX S BRAINARD AVE	320	ROBBERY	STRONGARM - NO WEAPON	SIDEWALK	FALSE	FALSE	433	4	10	55	3	1200444	1814473	2004	4/15/2016 8:55	41.645688	-87.542331	(41.645687844, -87.542330642)
HK419739	6/9/2004 6:45	137XX S BRAINARD AVE	820	THEFT	$500 AND UNDER	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	6	1200420	1814496	2004	4/15/2016 8:55	41.645752	-87.542418	(41.645751563, -87.542417673)
HK212760	3/1/2004 3:15	137XX S LEYDEN AVE	460	BATTERY	SIMPLE	SIDEWALK	FALSE	FALSE	533	5	9	54	08B	1180312	1814334	2004	4/15/2016 8:55	41.64579	-87.615987	(41.645789665, -87.615987256)
HK768578	11/22/2004 16:00	137XX S LEYDEN AVE	915	MOTOR VEHICLE THEFT	TRUCK, BUS, MOTOR HOME	STREET	FALSE	FALSE	533	5	9	54	7	1180312	1814334	2004	4/15/2016 8:55	41.64579	-87.615987	(41.645789665, -87.615987256)
HK121327	1/12/2004 5:00	137XX S BRAINARD AVE	810	THEFT	OVER $500	CTA GARAGE / OTHER PROPERTY	FALSE	FALSE	433	4	10	55	6	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK123433	1/13/2004 8:00	137XX S BRAINARD AVE	810	THEFT	OVER $500	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	6	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK231818	3/10/2004 8:00	137XX S BRAINARD AVE	810	THEFT	OVER $500	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	6	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK321896	4/23/2004 8:00	137XX S BRAINARD AVE	920	MOTOR VEHICLE THEFT	ATT: AUTOMOBILE	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	7	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK330727	4/28/2004 7:00	137XX S BRAINARD AVE	1310	CRIMINAL DAMAGE	TO PROPERTY	STREET	FALSE	FALSE	433	4	10	55	14	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK429728	6/11/2004 5:45	137XX S BRAINARD AVE	810	THEFT	OVER $500	APARTMENT	FALSE	FALSE	433	4	10	55	6	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK525150	7/15/2004 18:40	137XX S BRAINARD AVE	320	ROBBERY	STRONGARM - NO WEAPON	RESTAURANT	FALSE	FALSE	433	4	10	55	3	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK599648	9/2/2004 22:45	137XX S BRAINARD AVE	910	MOTOR VEHICLE THEFT	AUTOMOBILE	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	7	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK654940	9/28/2004 7:45	137XX S BRAINARD AVE	1320	CRIMINAL DAMAGE	TO VEHICLE	STREET	FALSE	FALSE	433	4	10	55	14	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK661598	10/1/2004 10:30	137XX S BRAINARD AVE	910	MOTOR VEHICLE THEFT	AUTOMOBILE	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	7	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK720700	10/28/2004 6:00	137XX S BRAINARD AVE	820	THEFT	$500 AND UNDER	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	6	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK731210	11/4/2004 11:15	137XX S BRAINARD AVE	810	THEFT	OVER $500	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	6	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK807017	12/13/2004 5:45	137XX S BRAINARD AVE	820	THEFT	$500 AND UNDER	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	6	1200405	1814512	2004	4/15/2016 8:55	41.645796	-87.542472	(41.645795847, -87.542472012)
HK218808	3/3/2004 23:45	137XX S BRAINARD AVE	820	THEFT	$500 AND UNDER	PARKING LOT/GARAGE(NON.RESID.)	FALSE	FALSE	433	4	10	55	6	1200397	1814520	2004	4/15/2016 8:55	41.645818	-87.542501	(41.645818001, -87.542501011)
HK276339	4/1/2004 17:23	137XX S BRAINARD AVE	051A	ASSAULT	AGGRAVATED: HANDGUN	RESIDENCE	FALSE	FALSE	433	4	10	55	04A	1200397	1814520	2004	4/15/2016 8:55	41.645818	-87.542501	(41.645818001, -87.542501011)
HK448150	6/22/2004 16:07	137XX S BRAINARD AVE	486	BATTERY	DOMESTIC BATTERY SIMPLE	APARTMENT	FALSE	TRUE	433	4	10	55	08B	1200397	1814520	2004	4/15/2016 8:55	41.645818	-87.542501	(41.645818001, -87.542501011)
HK464878	6/30/2004 13:45	137XX S BRAINARD AVE	3960	INTIMIDATION	INTIMIDATION	RESIDENCE	FALSE	TRUE	433	4	10	55	26	1200397	1814520	2004	4/15/2016 8:55	41.645818	-87.542501	(41.645818001, -87.542501011)
HK472024	6/25/2004 17:00	137XX S BRAINARD AVE	4387	OTHER OFFENSE	VIOLATE ORDER OF PROTECTION	APARTMENT	FALSE	TRUE	433	4	10	55	26	1200397	1814520	2004	4/15/2016 8:55	41.645818	-87.542501	(41.645818001, -87.542501011)
HK551087	8/11/2004 14:16	137XX S BRAINARD AVE	890	THEFT	FROM BUILDING	RESIDENCE	FALSE	FALSE	433	4	10	55	6	1200397	1814520	2004	4/15/2016 8:55	41.645818	-87.542501	(41.645818001, -87.542501011)
HK590968	8/30/2004 11:25	137XX S BRAINARD AVE	620	BURGLARY	UNLAWFUL ENTRY	RESIDENCE	FALSE	FALSE	433	4	10	55	5	1200397	1814520	2004	4/15/2016 8:55	41.645818	-87.542501	(41.645818001, -87.542501011)
HK734573	11/6/2004 12:00	137XX S BRAINARD AVE	460	BATTERY	SIMPLE	RESIDENCE	FALSE	FALSE	433	4	10	55	08B	1200397	1814520	2004	4/15/2016 8:55	41.645818	-87.542501	(41.645818001, -87.542501011)
HK625025	9/14/2004 21:00	003XX E 137TH ST	890	THEFT	FROM BUILDING	OTHER	FALSE	FALSE	533	5	9	54	6	1180674	1814353	2004	4/15/2016 8:55	41.645834	-87.614662	(41.645833532, -87.614662302)
HK213156	3/1/2004 7:00	003XX E 137TH ST	1750	OFFENSE INVOLVING CHILDREN	CHILD ABUSE	OTHER	TRUE	TRUE	533	5	9	54	20	1180691	1814354	2004	4/15/2016 8:55	41.645836	-87.6146	(41.645835887, -87.614600077)
HK429471	6/13/2004 9:00	003XX E 137TH ST	890	THEFT	FROM BUILDING	RESIDENCE	FALSE	FALSE	533	5	9	54	6	1180691	1814354	2004	4/15/2016 8:55	41.645836	-87.6146	(41.645835887, -87.614600077)

The crime types collected include two forms of violent crime and two forms of property crime:

VIOLENT CRIME	PROPERTY CRIME
Street Robbery	Residential Burglary
Aggravated Assault	Auto Theft

These crime types were selected because they are commonly analyzed by policing agencies for the purposes of reducing crime (Chainey, et al. 2008).

While each city's crime data contains a different number of attributes, there are common variables across all three cities within the data that may be extracted for analysis. Since the police data are categorized as Part I by the Federal Bureau of Investigation, the unifying attribute is the Uniform Crime Report (UCR) code. This was used to match crime types across the data. The UCR codes were inconsistent through all three cities, thus substantial cleaning was required to get the tables into a unified useable format for analysis. Atlanta's data contains 33 variables, whereas Chicago's data only contains 20 variables.

Seattle's crime data contains 17 variables. The exact address is obfuscated and given as a block address; therefore, the precise latitude and longitude are also generalized to the nearest hundred block address. While this did present a problem with precision, the locations were close enough for analysis purposes.

All crime data sets contained geolocation coordinates for each address. However, some of the data for Atlanta and Chicago missing XY coordinate information needed to be geocoded using a batch process. For analysis, it was most expedient to use the geocoder at Texas A&M (Goldberg 2015). This geocoding service outputs a file with the XY coordinates and the process to obtain them uses rooftop, street address, and other ancillary information. The geocoder could not be used on records that had no address information; therefore, those records were removed from the dataset. The total number of records removed from the Atlanta crime dataset was 441. The total removed from Chicago was 1241.

It is important to note that Atlanta experienced a change in their data collection methods. When the Atlanta Police Department redrew their administrative policing boundaries in 2011, the department did not immediately update their Records Management System (RMS) with the new boundary information. As a result, there were approximately 18 months of spatially inconsistent data when using the new boundary system. For this study, however, no police administrative boundaries were used for analysis, so the aforementioned was of little issue. The assumption was that the city polices according to a shared philosophy. As such, the boundary change did not create a greater problem when analyzing data over the ten-year period. The same could be said for Chicago, regarding policing boundary changes. However, if by reallocating personnel there was a change in patrol patterns, that could have affected the occurrence and dispersion of crime events.

All individual identifiable information was excluded from the study to comply with university IRB research privacy guidelines. This study did not include any data coded as crimes against children, sex crimes (to include Attempted Rape) or domestic violence. Because the study included Aggravated Assault counts, additional precautions were undertaken to ensure that reported domestic violence incidents were excluded from analyses.

3.1.2 Limitations of Crime Data

These data contain some limitations. Precise times were difficult to pinpoint, as property crimes often occur when the victim was away from home and violent crimes may be reported following victim hospitalization. This could be anywhere from one hour to one month or longer. In addition, many of the unknown shift times recorded occurred over a weekend or a one-week period and some crimes were simply not reported (Ratcliffe 2000). This study examined only reported crimes, their location, and the estimated times of occurrence as reported to the police. Reported crimes with unknown times of more than 24-hours were not included in the computations. This had more to do with an insignificant contribution to the overall distribution of the data (Ashby and Bowers 2013), rather than a simplification of the calculations themselves (Gottlieb et al. 1994).

Dallas, Texas was initially part of this study. The location had to be excluded and replaced with Seattle because the data were unreadable by machine. What this means is that in the address, which was the exact address was unable to be resolved using software due to the format of the address. For example, instead of an address reading:

1234 S Main St, Dallas, TX, 70123

The address read:

1234SMainStDallasTX70123

There were more than 1,000,000 records in total, and while not an impossible task, it would have been extremely time consuming to go through and correct each recorded address manually. Additionally, the police data for Dallas was no longer publicly available, which was an important component for this study. The decision was made to remove Dallas from the study and select a new study site so there would still be three locations for the research.

Seattle was chosen to replace Dallas because the police datasets were comparable to the data for Atlanta and Chicago, meaning the data had location, type of crime and reported date and time. The police data was also publicly available. There were, however, some problems with the data worth noting. Only six years of data were available for analysis from the Seattle Police Department, as opposed to the ten years from the other two cities. It was determined that the analyses could still produce relevant results.

The Seattle Police Department began transitioning from the Uniform Crime Reporting (UCR) style of records management to the National Incident-Based Reporting System (NIBRS) coding in the early 2000s. With NIBRS, there was no differentiation between residential and business offenses in the Burglary/Breaking and Entering category (U.S. Department of Justice 2011). Under the UCR Program, residential and business burglaries were individual subcategories of Burglary and could be separated for more precise analysis. Since the two distinctions could not be determined with the change in the data recording, the analysis was performed with all incidents in the Burglary category.

The same issue occurred with Robbery in Seattle. Under the UCR Program, there were several subcategories for Robbery. Specifically, there was a code for Highway Robbery (or Street Robbery) and Business Robbery (e.g., banks and liquor stores). That was no longer the case with NIBRS. As such, all robbery was included for analysis in the category of Robbery.

Including all incidents in the two categories with Seattle's data created questions of accuracy; however, short of pulling every police report for Burglary/Breaking and Entering and Robbery, there was no way to determine what offenses involved residential or business nor what offenses were against a person or property.

Chicago crime data does not distinguish between business robbery and highway robbery. The same is true for residential burglary and business burglary. Therefore, all burglary and all robbery counts will be included. Additionally, the category of Assault was quite limited, as assaults against police officers and protected employees were parsed out and some assaults were put into other categories like Battery. Assault and battery are generally a single category in the other policing jurisdictions; therefore, they were combined to create one category of assault for this study.

3.1.3 Census and Economic Data

Socio-economic attributes were collected from census enumerations, to include American Community Survey (ACS) and Economic Survey data. Social and economic data were also collected from CityData.com, which uses census and ACS data downscaled to the neighborhood level. Authoritative census data was collected from each city via their Open Data Portal. Much of the descriptive analysis is at the neighborhood scale, which is a slightly finer resolution than block groups. The need for the ACS and Economic Survey data was because they both covered the years between the decennial enumerations as well as provided an overview of the socio-economic changes that occurred during the recession period from 2007 to its official end in 2012.

3.1.4 Transportation Data

Public transportation, namely stops for buses, trolleys and metro rails, have been correlated with violent and property crime (Roncek and Maier 1991), and have been viewed as crime generators (Brantingham and Brantingham 1995). The clustering of crime in these locations has been the focus of past and recent research (Levine and Wachs 1986; Eck et al. 2007; Hart and Miethe 2014). This particular dataset contains the aforementioned types of public transportation along with discrete stop-location data to determine whether such correlations exist in the study areas. Additionally, analyses at the finer resolution of street segments have been shown to be of benefit when examining localized crime phenomena with longitudinal data (Weisburd et al. 2012; Curman et al. 2014; Hart and Miethe 2014).

3.1.5 Satellite Imagery

While the use of remote sensing techniques may prove greatly useful in determining changes in the landscape over time, the labor-intensive process would be detrimental to a timely completion of the research, and therefore was not undertaken. However, imagery will be used for qualitative comparative analyses and to highlight overt longitudinal changes in the landscape, which proved to be a factor in the decline and/or increase of crime events in a respective location.

3.2 Study Areas

The police jurisdictions chosen for this work were representative of three different U.S. regions, the West, Midwest and South as defined by the U.S. Census Bureau (Figures 1-2). Since the regions differ from each other, the significance of finding direct similarities in both spatial and temporal attributes has the potential to impact the methods used to analyze institutionalized clustering of crime events. What I mean by institutionalized clustering are areas of a city with persistent clustering of crime over several years with little or no change in magnitude.

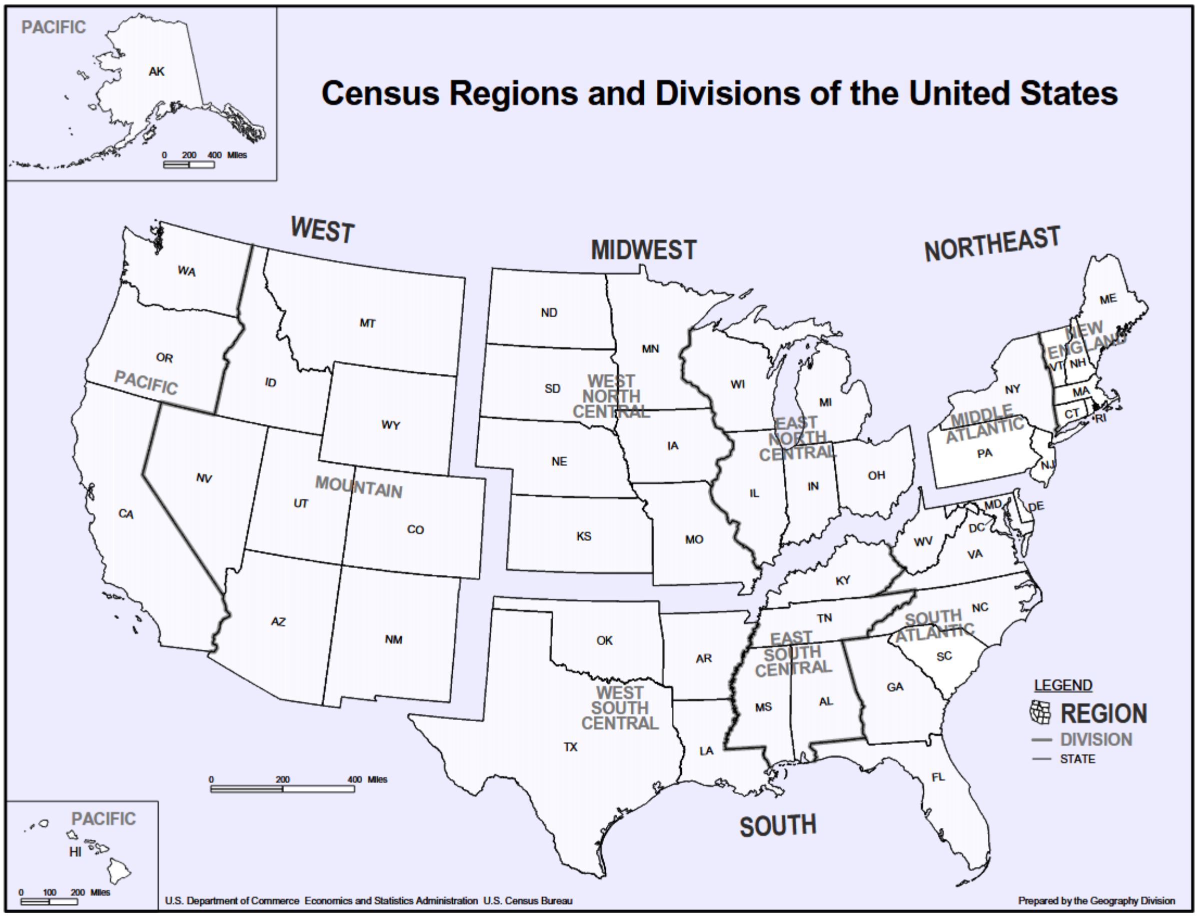

Figure 1. US Census Bureau Regions and Divisions

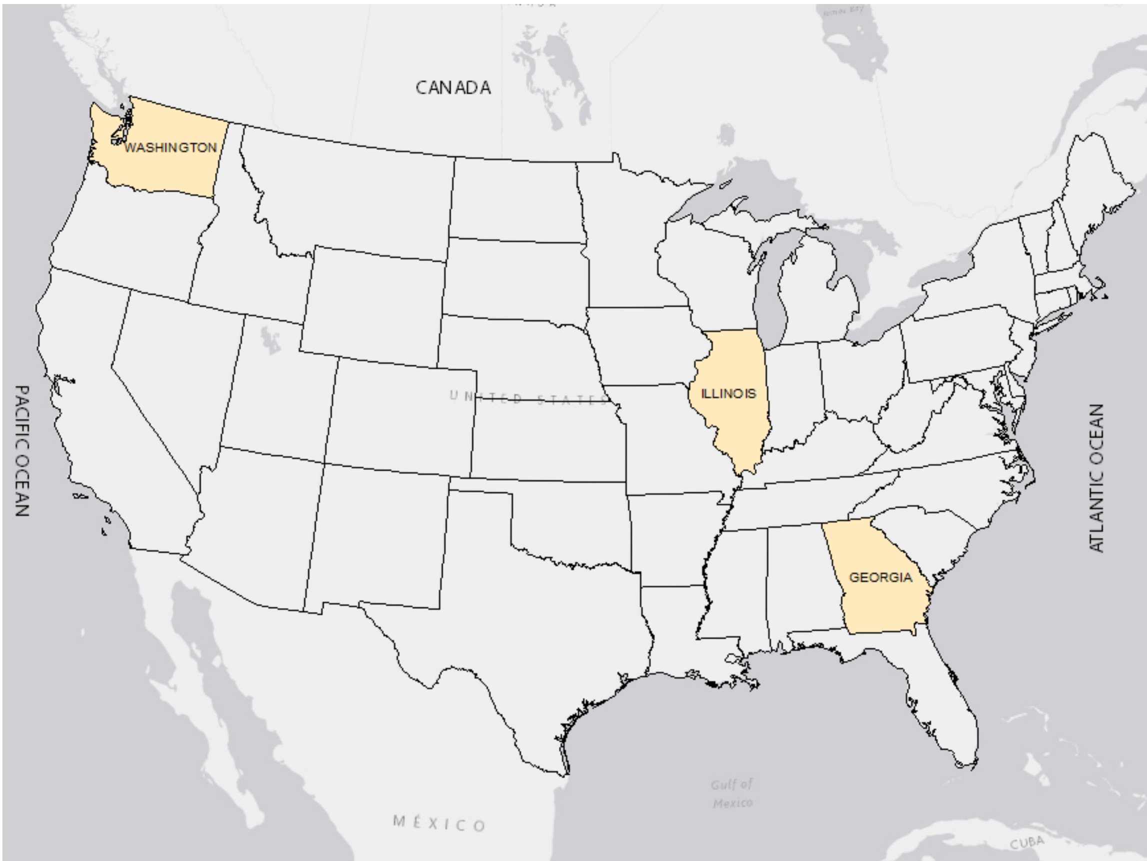

Figure 2. Regional study locations

To utilize a standard naming convention for neighborhood community types in each city, ESRI Tapestry Segmentation was used (Appendix B). The Tapestry Segmentation provided a detailed description of "[U.S. neighborhoods dividing] residential areas into 67 distinct segments based on their socioeconomic and demographic composition – and further classifies the segments into LifeMode and Urbanization groups" (ESRI 2015, 3). The segments were based on the US consumer markets, which ESRI then "combined into summary groups based on lifestyle and lifestage composition" (ESRI 2012, 3). In 2012, the Tapestry Segmentation included 65 segments, 12 LifeMode Summary Groups and 11

Urbanization Summary Groups. From 2014 to the present, it has been 67 segments with 14 LifeMode and 6 Urbanization groups.

3.2.1 Atlanta, Georgia

The City of Atlanta is located in the mid-section of Fulton County in the southern state of Georgia (Figure 3a-b). It played host to the 1996 Summer Olympic Games and is the longstanding corporate headquarters for the Coca-Cola Company, and Cable News Network (CNN). Atlanta was founded in 1837 at the end of the Western and Atlantic railroad lines. It was recognized in 1868 as Georgia’s premier city, after which the state’s capital was moved to the fast-growing city (Wortman 2009). Atlanta endured two citywide burnings in its early years of development during and after the Civil War. It was first christened Marthasville in 1843 to honor the daughter of the former governor, Wilson Lumpkin. Two years later, in 1845, the name was changed to Atlanta, supposedly the feminine version of the word Atlantic (Wortman 2009).

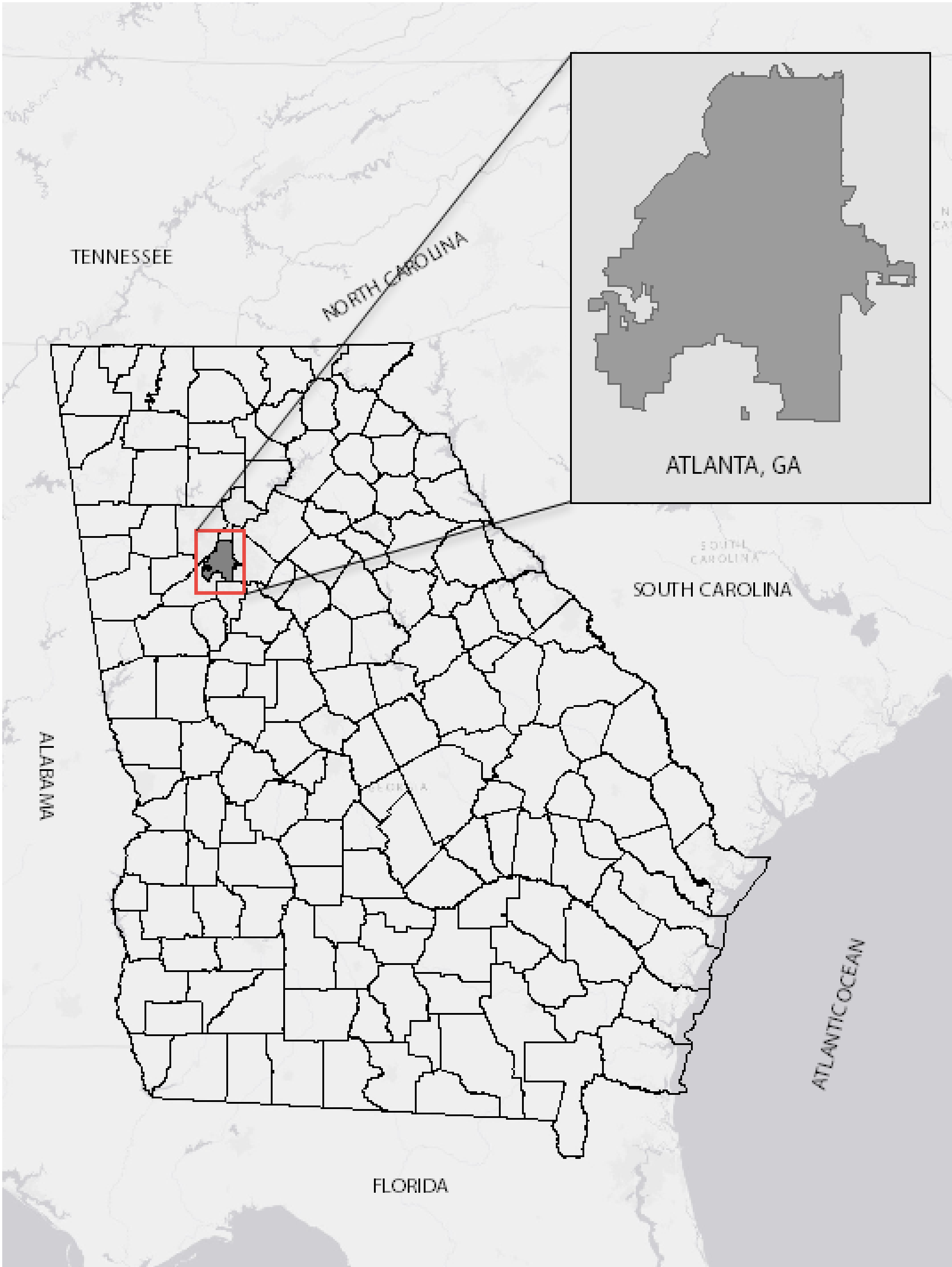

Figure 3a. State of Georgia with city of Atlanta

Atlanta encompasses an area of approximately 132 square miles and is bordered on the north by the suburban city of Sandy Springs; DeKalb County makes up the eastern border of the city; Cobb County is west, and the southern border is Clayton County (Fulton County GIS). The city is comprised of 25 Neighborhood Planning Units, which include 101 Neighborhood Statistical Areas (NSAs). The NSAs were created by the Atlanta Regional Commission to provide a consistent method of planning for the city, which has 240 named neighborhoods (259 total micro areas). With an estimated population of 420,325 people in 2000 and 420003 in 2010, the city of Atlanta ranked as the 39th-largest and 38th-largest in the United States (U.S. Census Bureau 2000, U.S. Census Bureau 2010). Its elevation ranges from 225 to 320 meters.

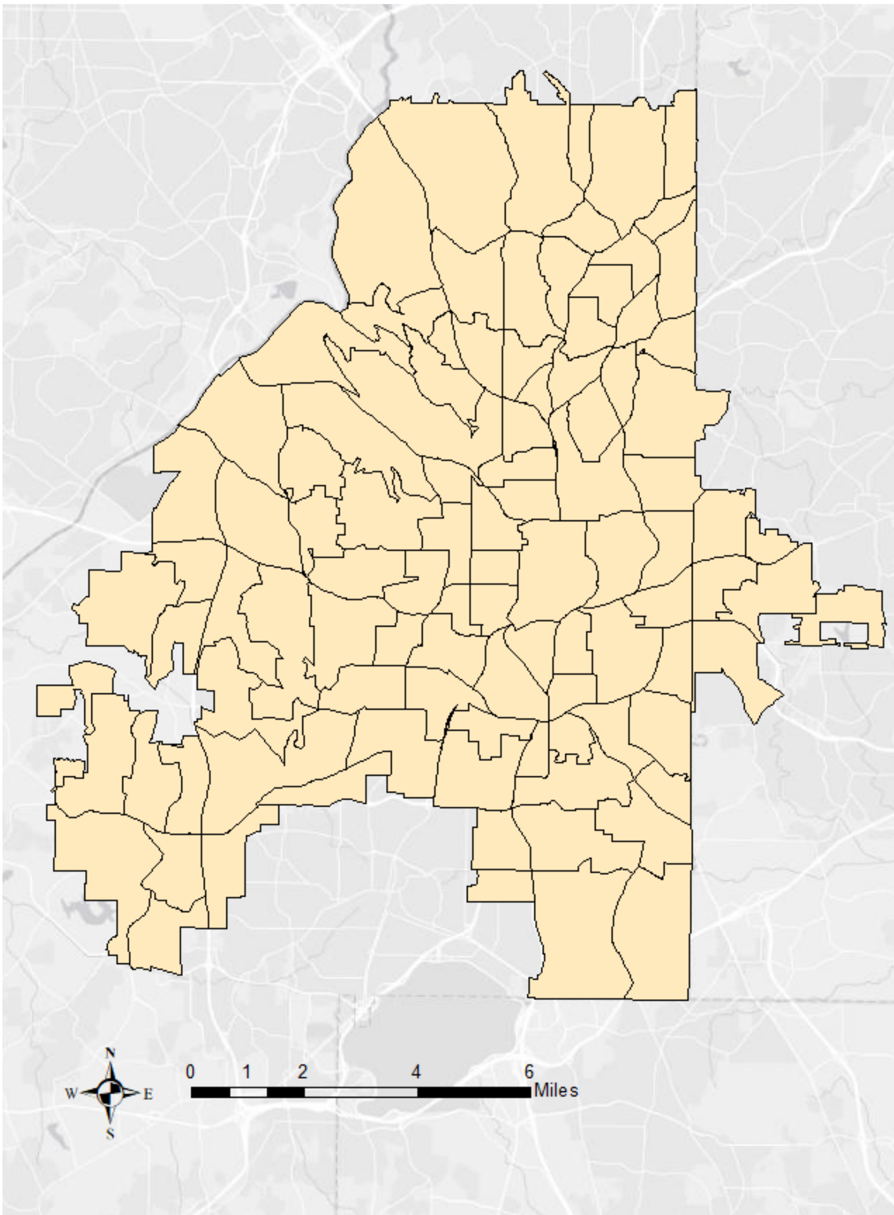

Figure 3b. City of Atlanta with neighborhood administrative units

There was an overall population increase for the city by 9.7% from 2006 to 2008 (Atlanta PD UCR), accounting for an additional 102,350 persons. In the two years prior to 2006, the increases were relatively steady fluctuating within a 1000-person loss-gain. The growth of the population figures for 2006 could be contributed to displacement caused by Hurricane Katrina, which greatly affected the South in August 2005. According to a report released by Appleseed, “at least 100,000 people evacuated to Atlanta in the days before and after Hurricane Katrina made landfall last August. The vast majority of these evacuees remain in the Atlanta area today” (Arrington, et al. 2006, 4). The reason for continued growth in the city has been yet to be determined, especially when considering the economic crisis that occurred just two years later.

The Tapestry Segment named “Metro Renters” was the predominant segment with 30.8 percent of all households. The median household income was about $67,000, though the median net worth was about $21,000. In this segment, nearly 80 percent of residents rent or share housing and the median age is 32.5.

“Modest Income Homes” was the second most predominant segment with 9.3 percent of households. The median age is 37 and most workers are in the Office and Administrative Support sector. The median household income is $23,900, while the median net worth is $12,400. Approximately 55 percent of residents in this segment rent and just over 44 percent are homeowners.

The “City Commons” segment was third with 9 percent of total households. The median age is 28.5. The median household income is $18,300 with the net worth at about $9,800. For comparison, the US median net worth is $93,300. This segment has mostly young, single, or single-parent households. About 77 percent of residents in this segment rent with only 23 percent experiencing homeownership.

3.2.2 Seattle, Washington

Seattle is a seaport city on the West Coast of the United States and is the largest city in the State of Washington and the Pacific Northwest region (Figure 4a). It was the location of the 1962 World’s Fair. According to U.S. Census data released in 2011, the Seattle metropolitan area population was an estimated 3.5 million, making it the 15th-largest metropolitan area in the U.S. In July 2013, Seattle was the fastest-growing major city in the United States with an annual growth rate of about 2.1 percent. The City of Seattle itself had an estimated population of 563,374 in 2000 with a ranking of 23rd-largest city in the United States (U.S. Census Bureau 2000) and 608660 in 2010 (U.S. Census Bureau 2010), with a ranking of 22nd-largest city.

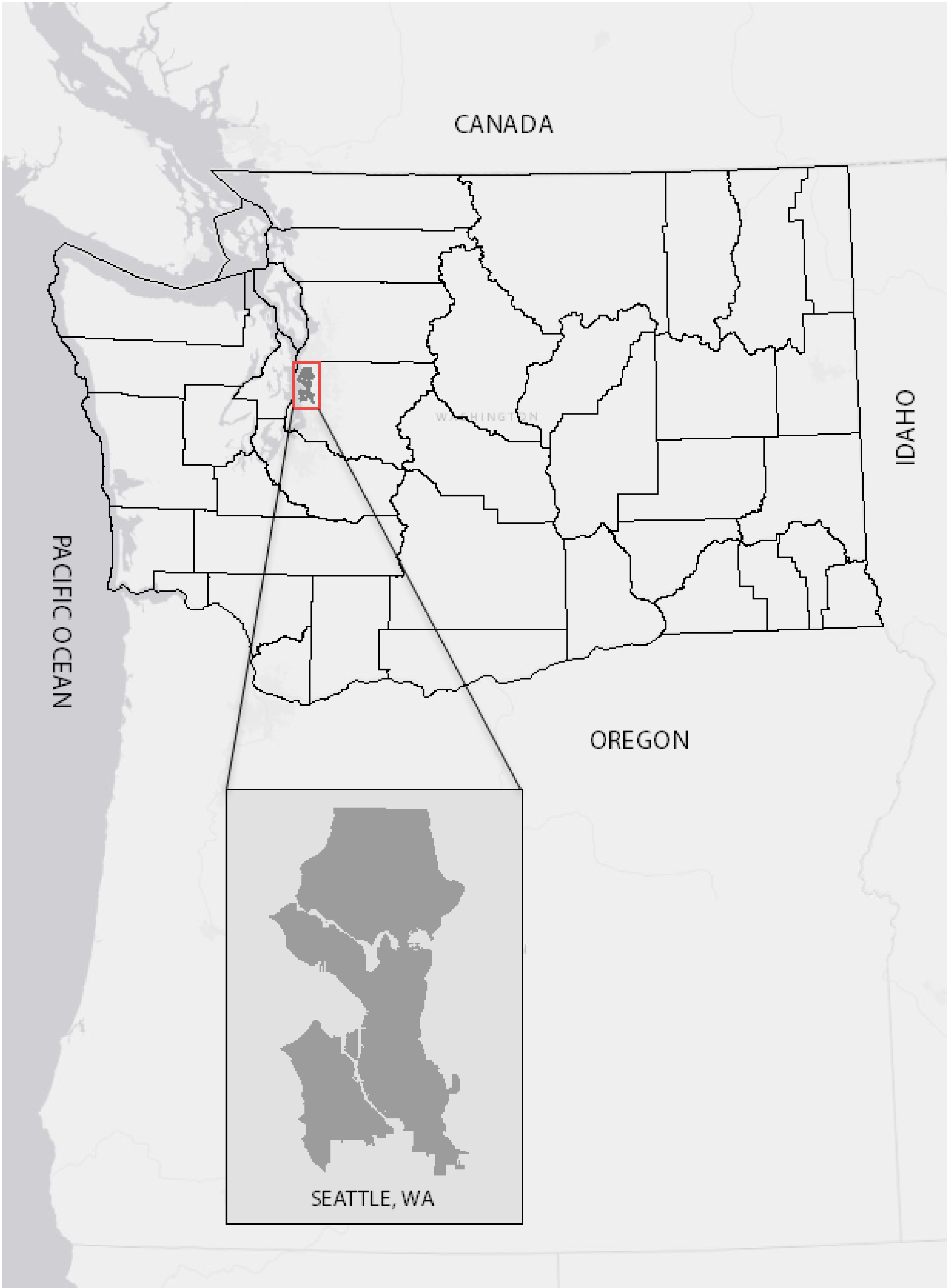

Figure 4a. State of Washington with city of Seattle

The City of Seattle, located in King County, is bounded by water to the east (Lake Washington) and west (Puget Sound). The city (land) is approximately 217 square kilometers and its elevation ranges from 0 feet to approximately 158m. There are 91 named neighborhood communities and 31 districts (Figure 4b).

Figure 4b. City of Seattle with neighborhood administrative units

The top three Tapestry Segments are “Metro Renters”, “Urban Chic”, and “Emerald City.” The city’s median household income is $100,589 with 66 percent of residents holding a bachelor’s degree or higher. The overall median age is 37.8. “Metro Renters” makes up 29.5 percent of all households.

The “Urban Chic” segment comprises 16.1 percent of households with a median age of 43.3. Nearly 40 percent of households in this segment receive their income from investments. The median household income is approximately $109,400 with the median net worth at about $303,000. Home ownership is above US average at 66.2 percent. This is a well-educated segment with more than 65 percent of residents holding a bachelor’s degree or higher. Most of these neighborhoods are suburban or coastal.

The “Emerald City” segment is 9.5 percent of total households. The median age is 37.4 for these residents with a median household income of $59,200 and a net worth of $52,700. Slightly more than half of homes are renter occupied at 51.5 percent.

3.2.3 Chicago, Illinois

The City of Chicago had the third largest population in the United States in both 2000 and 2010, with an estimated population of 2,896,016 and 2,695,598 respectively (U.S. Census Bureau 2000, U.S. Census Bureau 2010). Its primary policing agency is the Chicago Police Department, with a patrol jurisdiction covering approximately 590 square kilometers. Chicago is part of Cook and DuPage counties, with the bulk of the city within Cook County boundaries. The eastern edge of the city is bounded by Lake Michigan (Figure 5a).

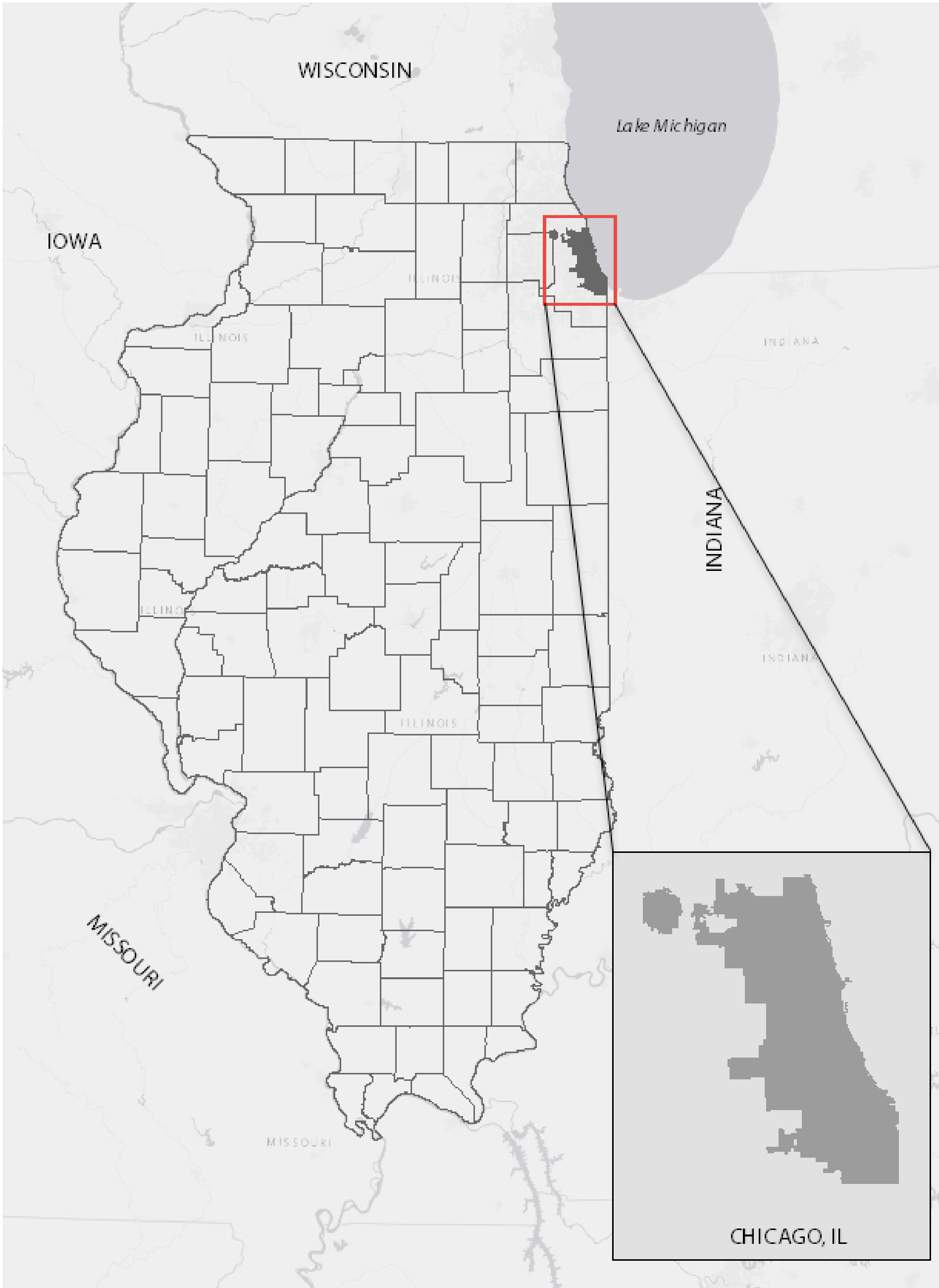

Figure 5a. State of Illinois with city of Chicago

Chicago is relatively flat with its highest elevation recorded at 205m and the lowest elevation at 175m. There are 75 community areas, not including O'Hare International Airport (the western most portion of the city), 158 neighborhoods, and 50 council wards, the latter of which has not changed in quantity since they were established in 1923 (Figure 5b).

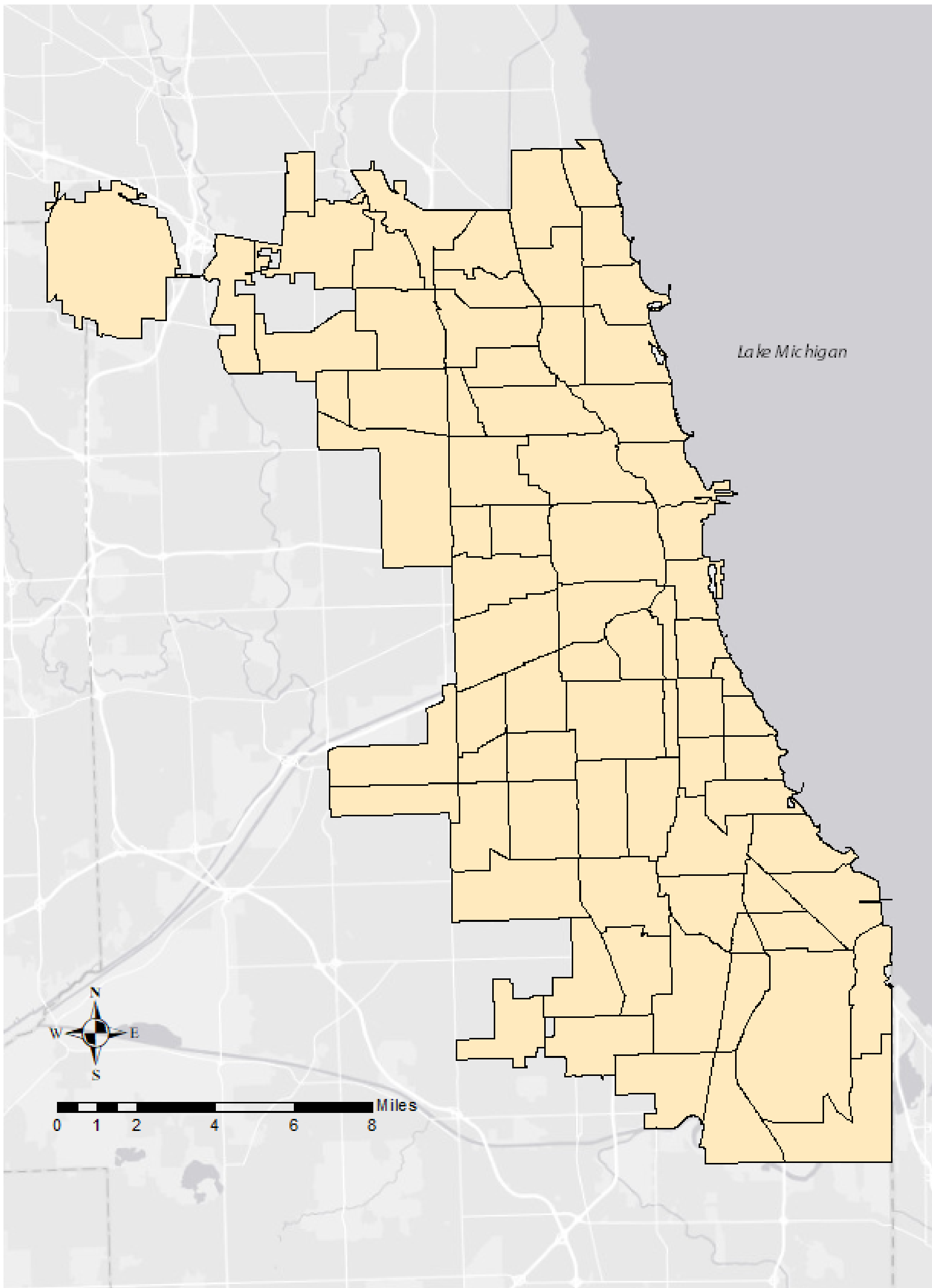

Figure 5b. City of Chicago with neighborhood administrative units

In the Tapestry Segments, "Metro Renters" tops this city with 16.3 percent of all households. The median age for the city is 35 and the median household income is $62,077.

The second segment is "Diverse Convergence" with 8.8 percent of all households. This segment is unique amongst the three cities in that it has nearly 40 percent of its population born abroad. The median age is 32.8 and the median household income is $46,500 with the net worth at $15,600. The primary occupations are office and administrative support, and 72.4 percent of residents are renters.

The "Trendsetters" segment are mostly singles living alone or with roommates. Approximately 75.5 percent of residents rent and have a median household income of $63,100. Their median age is 36.3 and their median net worth is $24,700. Most residents in this segment work in management.

3.2.4 Location Selections

Locations for study were selected from different regions because policing styles are not identical. Additionally, each of the jurisdictions had very unique histories, which may directly contribute to the manner in which crime clusters in those areas today. For example, the Hyde Park community in Southside Chicago experienced very little crime clustering, whereas just outside of the community, highly clustered criminal activity existed. Hyde Park is home to the University of Chicago, and residents in its immediate surrounding areas have a historically higher education and socio-economic status than some of the near-by communities.

The selection process depended upon the size of the city (population) and whether policing data was publicly available. If the data was available and it contained location data, the city was added to the list of possible study areas. Having one small, one medium and one large population city and having them in different geographic regions of the contiguous United States was the objective. It was in this manner that regionally it could be possible to determine if crime, regardless of location, displayed similar patterns.

Policing styles have regional differences as well. A very widely used program is Compstat, so called because it was a conjunction “for ‘computer statistics or ‘comparative statistics’ – nobody can be sure which” (Maple and Mitchell 2000). Developed in the early 1990s, Compstat was “a performance management system that is used to reduce crime and achieve other police department goals” (BJA 2013). Some agencies police according to a prescribed Compstat model like New York Police Department and Los Angeles Police Department, who were greatly influenced by the William Bratton philosophy of policing. Bratton was the Police Commissioner for NYPD and later the Chief of Police for LAPD. Other agencies subscribe to a modified version of Compstat, like Atlanta Police Department. There are agencies that do not use a Compstat model for policing (BJA 2013).

Moreover, not all agencies that use a Compstat model use it in the same way. For example, Daytona Beach and Baltimore Police Departments use Compstat for the purposes of offender apprehension. Other departments, like Clearwater, Florida, use the model for personnel accountability and budget review (BJA 2013). These differences will be examined to determine the level of disruption in high-density crime clustering.

Chapter 4. Methods

This study uses quantitative and qualitative spatial information and methods in response to the research questions. The qualitative information and methods aspect primarily involve the use of nominal and ordinal measurements in separating predictor and criterion variables into groups based upon their attributes. For example, taking the full crime dataset for a particular jurisdiction and separating the data into two large subgroups, property crime and violent crime, then within those large subgroups, creating additional subgroups, like robbery and homicide under violent crime and burglary and auto theft under property crime (Campbell, 1998).

A multivariate analysis approach was applied to answer the first question: What geographic factors are highly correlated with a change in reported crime and are these factors spatially and temporally similar for all three cities? Multivariate data is better suited for a computational approach, especially since much of the data have temporal and spatially lagged influences (Montello and Sutton 2013). It was necessary to use factor reduction methods for the initial discovery of highly correlated factors. While there are several types of methods used in pure computational situations, the method of ordinary least squares (OLS) was used to address the preliminary statistical analyses and geographically weighted regression (GWR) for the preliminary spatial analyses. While geographically weighted regression contains a spatial element, the temporal aspect remains unaddressed. To alleviate this issue, a series of choropleth maps were used for a preliminary examination to discover cluster-persistent areas within the jurisdictions.

Once the areas with persistent clusters were identified and the location characteristics had been thoroughly described, the factors from question one were used to answer the first part of the second question: *Which persistent clusters of crime cannot be explained by the factors revealed in Q1*?

The model developed to respond to the third question (*How can the factor-based methods used to answer Q2 be used to explain spatiotemporal patterns of crimes both over time and across/within the three cities*?) would be applied to all three locations to determine if similar inferences could be made using a single model.

4.1 Data Wrangling

Before any computations could occur, the data had to be preprocessed or wrangled into a usable format that was uniform across the three datasets. The crime data and much of the additional place data were already geocoded. Those data were downloaded as .csv files and standardized in Microsoft Excel before being converted back to .csv and imported into R. For import into ArcGIS, the Excel file was used.

Any data that did not already have spatial information was geocoded using Geoservices from Texas A&M (2015), if geocoding was possible. Geoservices were primarily used for data gathered from ReferenceUSA and other independent sources, which may have had no spatial reference. The remaining non-spatial data or attributes were either counted or used as descriptive data, except in the case of the crime data. Reported crime events with no spatial information were removed from the datasets. Atlanta and Seattle had minimal records removed; however, with Chicago, removed records ranged from 12,966 to 118,420 depending upon the year.

Crimes and other attribute data were aggregated to the neighborhood level, which was one level more detailed than the census block group level. This was done more for convenience of analysis before moving to a finer resolution for the specific areas that experienced sustained high-density events.

4.2 Computational Methods

The initial exploratory analyses included statistical analyses (e.g., summary statistics), ordinary least squares, and geographically weighted regression techniques. Those results were then integrated into a GIS for further analyses and visualization. The analyzed data included police calls for service (CFS) crime data, census socio-economic, street networks, business locations, land use, and housing vacancy rates. Calls for service (CFS) are the records of when people call the police for assistance, whether using the business line or dialing 9-1-1 for an emergency.

Geocomputation methods in the R-programming environment were also utilized for both statistical and spatial analyses. While R was used as a GIS, a portion of the geospatial data pre-processing was also conducted using ArcGIS. Additionally, for visual exploratory analysis, ArcGIS was used, as ArcGIS provided more flexibility in constructing mapped layouts. Both the R environment and ArcMap were used for the production of the final mapping products.

4.3 Spatial Methods

In response to both Q1 and Q2, it was necessary to perform spatial analyses, as mentioned previously. Where Ordinary Least Squares (OLS) offered a global computational perspective and exposed attributes that are spatially autocorrelated, Geographically Weighted Regression (GWR) alleviated many of those issues by calculating local spatial relationships. OLS provided the needed residuals to obtain initial correlations.

4.3.1 Ordinary Least Squares

Ordinary Least Squares (OLS) is the best-known method with which to begin a spatial regression analysis (Scott and Pratt, 2009). It is the global model of the process and uses a single linear regression equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_n x_n + \varepsilon$$

where y is the value of the observed dependent variable, $x_1, x_2, \ldots, x_n$ are the values of the observed independent variables, $\beta_0, \beta_1, \ldots, \beta_n$ are the parameters to be estimated (the coefficients), and ε is the residual or error term assumed to be normally distributed over space. The equation is obtained with (Fotheringham and Rogerson, 2009):

$$\beta' = (\mathrm{X}^T \mathrm{X})^{-1} \mathrm{X}^T \mathrm{Y}$$

OLS relies upon three critical characteristics: (1) the parameters are linear, (2) the residuals are assumed to be normally distributed, and (3) the scale of the predicted scores is in the same units as the dependent variable (Cohen 2003).

In checking the model for best fit, six indicators are examined: Coefficient and Koenker (BP) Statistic, Variant Inflation Factor (VIF), Akaike's Information Criterion (AICc) value, Jarque-Bera Statistic, Adjusted R-Squared value. Coefficients were tested for statistically significant variables at a 0.05 level. The Koenker test looks for regional variations (non-stationarity) of the spatial data relationships. The VIF value represents the acuteness of multicollinearity. If the variable's VIF value is greater than about 7.5, it means there is at least one other explanatory variable in the model that is telling the same story. The AICc is used to compare different models. The lower the AICc value, the better the model. Jarque-Bera tests for normality in the distribution. If this statistic is significant, then it means there is a key variable missing and the model is biased; therefore, the results are no longer reliable. A high Adjusted R-Squared value indicates the level of variance, or rather, how much of the model can be explained by the variation in observed dependent variable values. The higher the number, the better the model has performed.

4.3.2 Spatial Autocorrelation

The Global Moran's I Index measures the correlation of each neighboring feature. The index tests for randomness in the spatial distribution of model residuals. The Moran's I statistic for spatial autocorrelation is given as:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2}$$

where z_i is equal to $x_i - \bar{x}$. "The z's are then dispersed in one multivariate distribution such that the correlation between any two z's is $-(n-1)^{-1}$" (Moran 1948(b)). The spatial weight between features i and j is represented by $w_{i,j}$, n is equal to the total number of observations, and S_0 is the aggregate of all the spatial weights (ESRI 2011):

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}$$

The z_I-score is calculated as:

$$z_I = \frac{I - \mathrm{E}[I]}{\sqrt{\mathrm{V}[I]}}$$

where E is the expected value, and V is the variance (Borwoski and Borwein 2005). These can be found in Moran (1950, ESRI 2011):

$$\mathrm{E}[I] = \frac{-1}{(n-1)}$$

$$\mathrm{var}[I] = \mathrm{E}\left[I^2\right] - \mathrm{E}[I]^2$$

When the results of the calculations return a statistically significant p-value, the null hypothesis may be rejected, as a significant p-value would indicate spatial clustering of model residuals, not random patterns. P-values are statistically significant at 0.05, which indicates that the assumption of independence between observations has been violated. The areal units of measurement (census tracts, ZIP codes, etc.) are not functioning independently of each other to meet the expectation of observation independence; the neighborhoods are not distinct. Spatial autocorrelation is a common issue when using spatial data. Using statistical data collection neighborhood boundaries to analyze crime data contained regression error, as the variables (or predictors) applied to the analysis are observable, while the neighborhood boundaries themselves are unobservable (Dubin 1998). Therefore, a weighted regression method was used to help improve model selection.

4.3.3 Geographically Weighted Regression

When OLS suffers from spatial autocorrelation of the residuals in the initial determination of the explanatory variables, Geographically Weighted Regression (GWR) offers an alternative approach to traditional regression analysis by incorporating local spatial relationships. GWR is a tool that "allows the parameter estimates to vary over space" (Fotheringham 2009). Its linear equation is:

$$y_i = \beta_{0i} + \beta_{1i}x_{1i} + \beta_{2i}x_{2i} + \ldots \beta_{ni}x_{ni} + \varepsilon_i$$

where i refers to the locations at which data on y and x are measured (Fotheringham, 2009). Thus, the estimated coefficients are local rather than global, as was calculated in OLS.

A GWR model uses a distance-based weight function allowing locations closest to the point of estimation to carry a greater influence on the estimate (Cahill and Mulligan 2007). The weighted estimator is then represented by the following equation where $\mathrm{W}(i)$ is a matrix containing weights specific to location i (Fotheringham, 2009):

$$\beta'(i) = (\mathrm{X}^T \mathrm{W}(i) \mathrm{X})^{-1} \mathrm{X}^T \mathrm{W}(i) \mathrm{Y}$$

$$\mathrm{W}(i) = \begin{bmatrix} w_{i1} & 0 & \ldots & \ldots & 0 \\ 0 & w_{i2} & \ldots & \ldots & 0 \\ 0 & 0 & w_{i3} & \ldots & 0 \\ . & . & . & \ldots & . \\ 0 & 0 & 0 & \ldots & w_{in} \end{bmatrix}$$

While there are several methods used to calculate weights, ArcGIS uses Gaussian expressions for both fixed and adaptive weighting. This study used the adaptive function as represented by:

$$w_{ij} = \left[1 - \left(d_{ij}^2 / h^2\right)\right]^2 \quad \text{if } j \text{ is one of the } N\text{th nearest neighbours of } i$$

$$= 0 \quad \text{otherwise}$$

where h is the bandwidth and N is the parameter to be estimated (Fotheringham 2009). The rational for using the adaptive bandwidth is that the model can be largely affected by the degree of distance decay, which involves careful selection of an appropriate bandwidth. “If the bandwidth is too small, the number of data points used in estimation may become too low and result in instability in the parameter estimates” (Cahill and Mulligan 2007). If the bandwidth is too large, spatial variance is low and the GWR model begins to resemble the OLS model. To correct for the bandwidth sensitivity, the AICc option is used:

$$\text{CV} = \sum_i \left[y_i - y \neq i^*(h)\right]^2$$

where $y \neq i^*(h)$ is the fitted value of y_i with data from point i removed from the calibration and:

$$\text{AICc} = \text{Deviance} + 2k\left[n / \left(n - k - 1\right)\right]$$

where n is the number of data points and k is the number of parameters in the model (Fotheringham 2009). The GWR model for this study used an adaptive kernel method with a cross validation bandwidth.

4.5 Temporal Methods

Due to the manner in which the data were entered into the police records management system (RMS), offenses for December 31 may be pushed to the following year. This occurred in Atlanta. Additionally, when entering the shift time of occurrence, there was no consistency in how the shift was recorded, especially for Atlanta. Frequently, an event with a starting time of the previous evening and an ending time in the afternoon the following day was recorded as "morning", even though the day shift seemed more intuitive. Seattle has no shift reported, only the time. Therefore, for this study, shifts were standardized for all three jurisdictions. The 24-hour period was grouped into six-hour sections and re-categorized as "time frames" to be used for time-series analysis. This made the time frames:

Morning = 0001 to 0600

Day = 0601 to 1200

Afternoon = 1201 to 1800

Night = 1801 to 0000

Finally, there appeared to be occurrences of duplicate entries with unique incident numbers. Without viewing the actual written reports, it was difficult to determine whether there were in fact two separate events. For the purposes of this study, duplicates with unique incident (or report) numbers were treated as two separate events occurring at the same location. Adjustments were made for the calculations and counts; however, the inaccuracies left a negligible margin for error.

4.6 Scales of Analyses

Scale became an issue during the analysis phase of the study. Each region has its own administratively defined policing boundaries that do not always follow the census block design. The more pressing problem was working with a cross-level fallacy (Montello 2015), as both disaggregated and aggregated data were used to make inferences using statistical data collection areas defined by each city. These areas then became the neighborhoods used for analysis, which were larger than the census block and in most cases larger than the block-group.

According to the U.S. Census Bureau, census blocks are defined as "statistical areas bounded by visible features such as roads, streams, and railroad tracks" (2011). Census blocks may also be bounded by property lines, city, township, school district and county limits. Within law enforcement, blocks are typically delineated by street segments, though the administrative boundaries may very closely resemble census block delineations. Cities will also create administrative boundaries that follow street segmentation, however, the neighborhood boundaries created are not generally the same as a policing boundary or a resident-defined neighborhood boundary. Using different areal units for analysis can be problematic.

The Modifiable Areal Unit Problem or *MAUP* is an issue with scale and aggregation when performing quantitative studies in spatially related geography. "The term *MAUP* was coined by Openshaw and Taylor [in 1979] when they experimented with how correlation coefficient values changed when smaller areal units were aggregated to form larger areal units whether hierarchically or non-hierarchically" (Wong 2009, 105).

There are two types of *MAUP*. The zoning problem deals with inconsistencies in data based upon varying zoning systems; and the scale problem, which is associated with inconsistencies in geographic scale or spatial resolutions (Wong 2009). This research used statistical data at varying levels of scale, so it was not immune to potential errors when aggregating up to a larger unit of measure. For example, the administrative boundaries for the city of Atlanta were located in two different counties. It was necessary to combine both Fulton and DeKalb County geographies to obtain a complete picture of the city's census data. However, once the city boundary was clipped from the resulting two-county merge, there was most assuredly error in accounting for total population for each smaller policing area that bisected the merged county boundary.

The temporal resolutions for the discrete crime data were relatively consistent across all three areas. Deciding on an appropriate temporal scale for imagery and other non-crime data that matches with temporal aspects of the census data was a challenge. Captured imagery from Google Earth Pro was inconsistent for the years covering the study. There were images blocked by low cloud cover and the imagery were generated from different providers, like Landsat, and the US Department of Agriculture.

For this study, analyses were completed at three resolutions. The first was at the citywide level for a general overview, the second was at the neighborhood/community level, and the third was at a small grid level using the Fishnet tool in ArcGIS. The grids provided a more homogeneous method for area selection than a kernel density or point density analysis, because a grid contained uniform boundaries, unlike census block boundaries.

Census block size is not uniform across the United States. It is location-based and may not remain the same for each census enumeration year (U.S. Census Bureau 2011). Block size is not even standard within a neighborhood. For example, in Figure 6, census blocks in the Atlanta Neighborhood Statistical Area of Vine City, which is located west of the center of the city, were not uniform despite the neighborhood's grid-style layout.

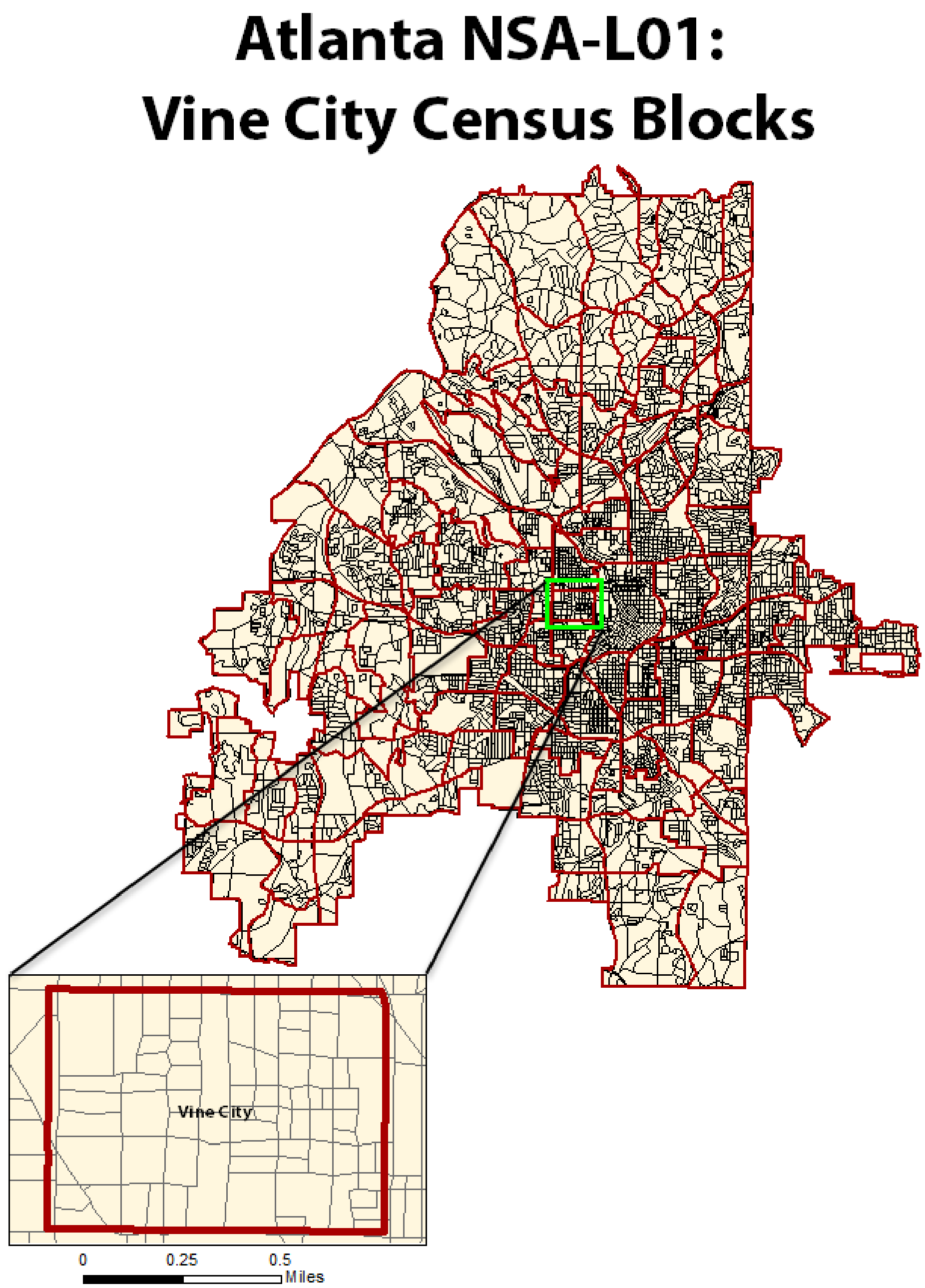

Figure 6. Vine City Neighborhood Statistical Area showing non-uniform census blocks

To further illustrate this concept, Chicago, a city where a majority of the landscape has a grid layout, did not have consistently uniform census blocks within its Community Areas. This could be seen in areas like Belmont Cragin, one of the most densely gridded neighborhoods with 1088 census blocks (Figure 7).

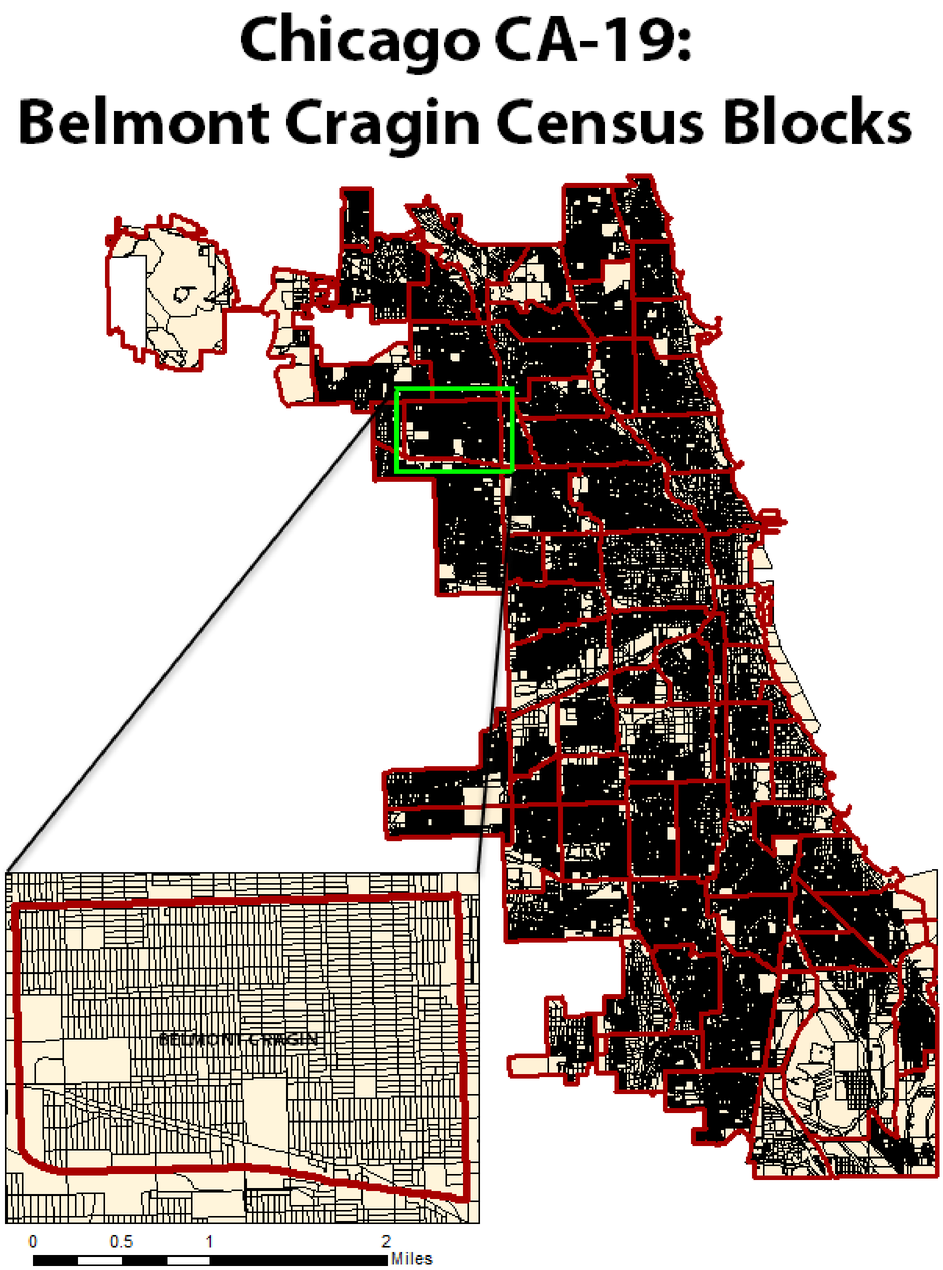

Figure 7. Belmont Cragin Community Area showing non-uniform census blocks

Census blocks in Seattle exhibited the same phenomenon. In viewing what appeared to be a neighborhood with uniform census blocks, a closer inspection of Whittier Heights shows that the block sizes were not all the same (Figure 8).

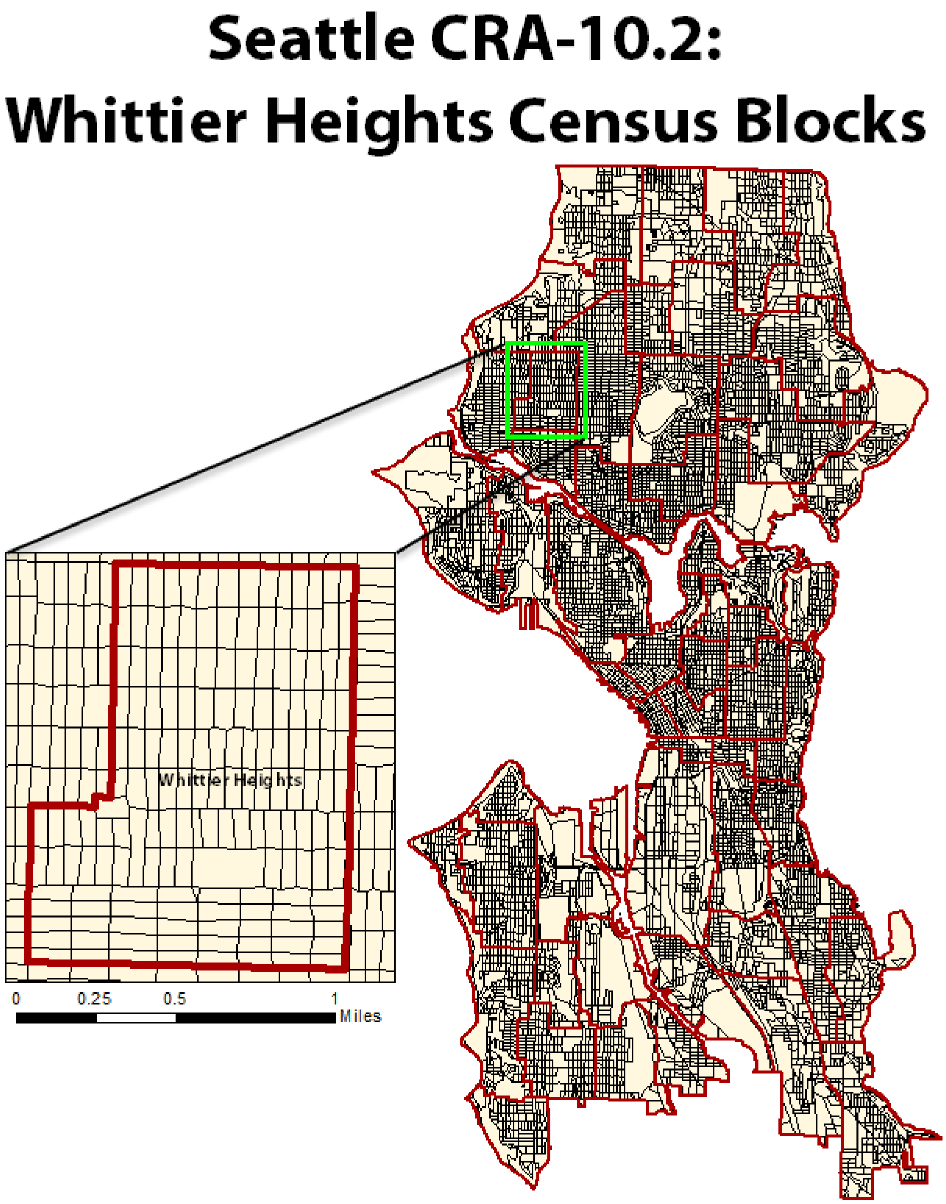

Figure 8. Whittier Heights Community Reporting Area showing non-uniform census blocks

Consequently, using census blocks to make a comparison across all three cities would not have been suitable, even though each city's crime point data was being used for the more granular analysis.

Using the fishnet (or grid) method, a count of the discrete data was assigned to each grid, thereby offering a method of verification beyond visual analysis alone. The size of the grid cell used was 1320 feet by 1320 feet for each city. The average size of the street segments in each city, which was approximately 425ft; however, using it as the guideline for grid cell size would make it difficult to detect spatial patterns given the overall size of each area analyzed (Chainey and Ratcliffe 2005). Chicago had the most consistent block layout throughout a large percentage of the city, with blocks of approximately 660 feet by 330 feet. Therefore, Chicago's block size was selected to serve as the standard grid size. By doubling the grid size to 1320 feet (.25 mi), it created an area that was approximately 2 by 4 blocks, depending upon the orientation of the blocks in the respective sections of the city. Ultimately, the larger area provided a functional standard area size for all three cities.

Although using a grid approach creates a visually unappealing map (Chainey and Ratcliffe 2005; Chainey, et al. 2008; Eck, et al. 2005), it was the best option for smaller area analysis, given the varying census block sizing.

4.7 Model Development for Analyses

Developed models were expected to be dynamic, allowing time to have an explicit representation, meaning "values for the dependent and explanatory variables [can be] indexed by spatial as well as temporal coordinates" (Rey 2015, 789). Code developed for this study is included in Appendix A.

Chapter 5. Analysis Results

The results are described by type of analysis (e.g., maps and box plots, OLS and temporal) and by city (ordered by population size). A more comprehensive discussion of the interpretation and significance of the results are presented in Chapter 6.

5.1 Initial Analysis

Choropleth maps and box plots provided an initial visual interpretation of the general crime overview of each year in each city. They were created using neighborhood/community statistical administrative boundaries defined by each city with a rate calculation of crimes per 1000 persons.

5.1.1 Atlanta

In viewing the choropleth maps (Figures 9a-9c), there were many neighborhood areas with persistently high rates of crime. Additionally, 2008 appeared to be a year with the higher rates across the largest portion of the city, covering approximately 43% of the neighborhood areas. It was also apparent that the northwest neighborhoods consistently experienced low rates of crime. Those neighborhood areas comprised the majority of the wealth in the city with six of the eight areas having a median household income between $95,000 and $141,000 (Atlanta Regional Commission 2014).

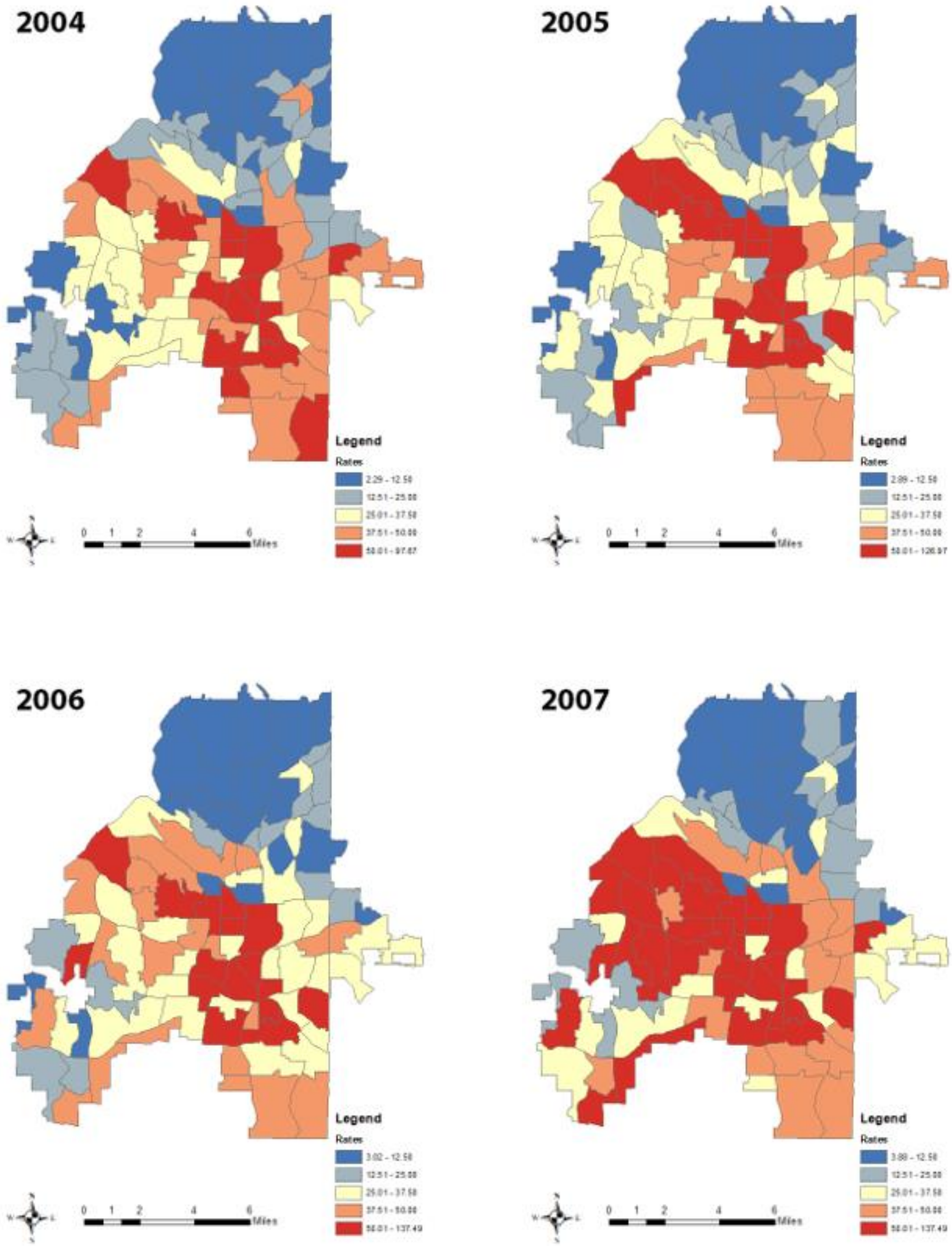

Figure 9a. Atlanta crime rates per 1000 by neighborhood area, 2004-2007.

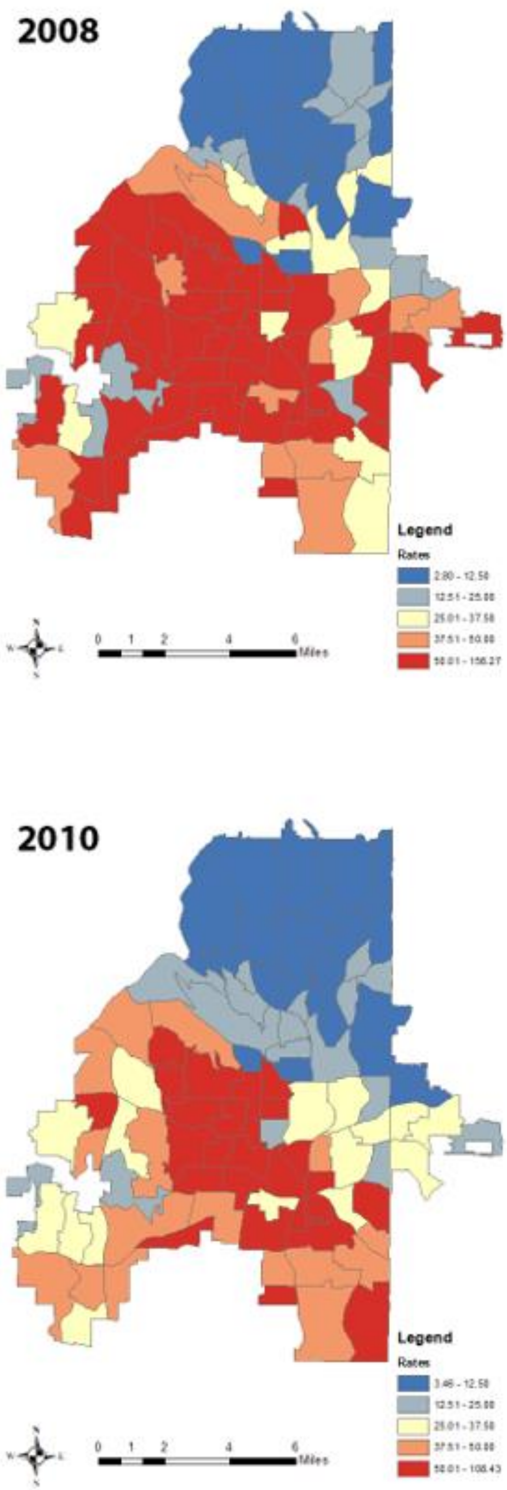

Figure 9b. Atlanta crime rates per 1000 by neighborhood area, 2008-2011.

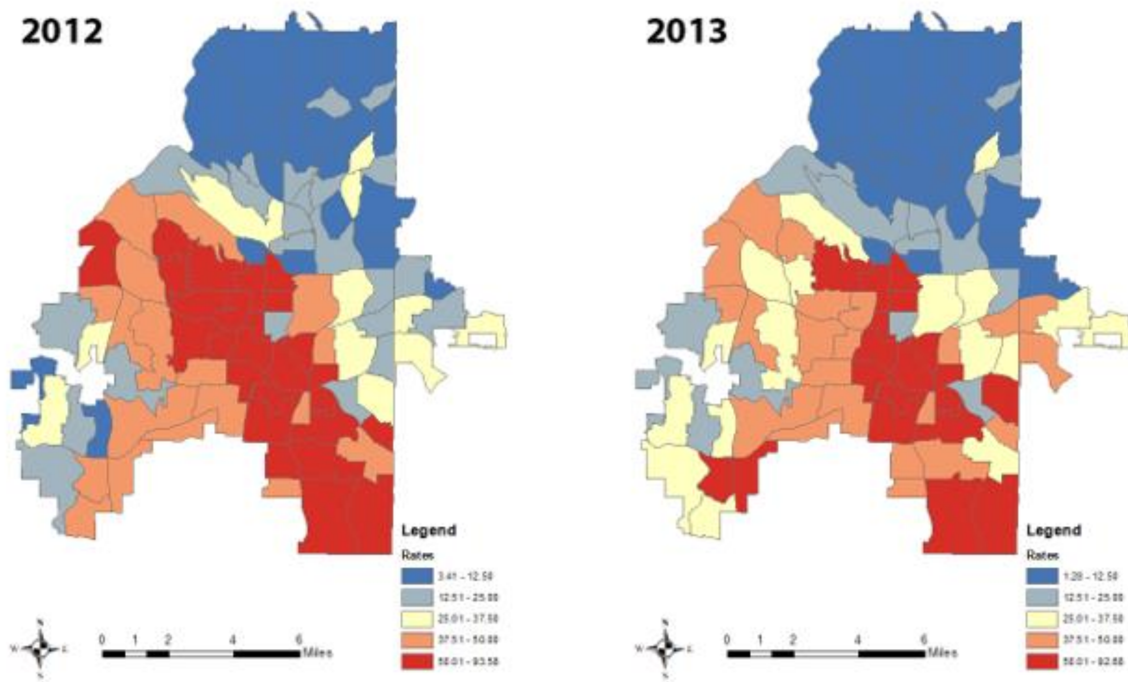

Figure 9c. Atlanta crime rates per 1000 by neighborhood area, 2012-2013.

The box plots (Figures 10a-10d) using absolute numbers, show that overall, from year to year the median is quite low for each crime type. The higher numbers are in the outliers. Property crimes were generally higher, especially Burglary (Figure 10b), than Aggravated Assault, Robbery, and Auto Theft. The data do not appear to be normally distributed and are positively skewed due to the lower boundary of the data (which is zero), as seen in the number of outliers and the extended whisker between the 75th percentile and the maximum.

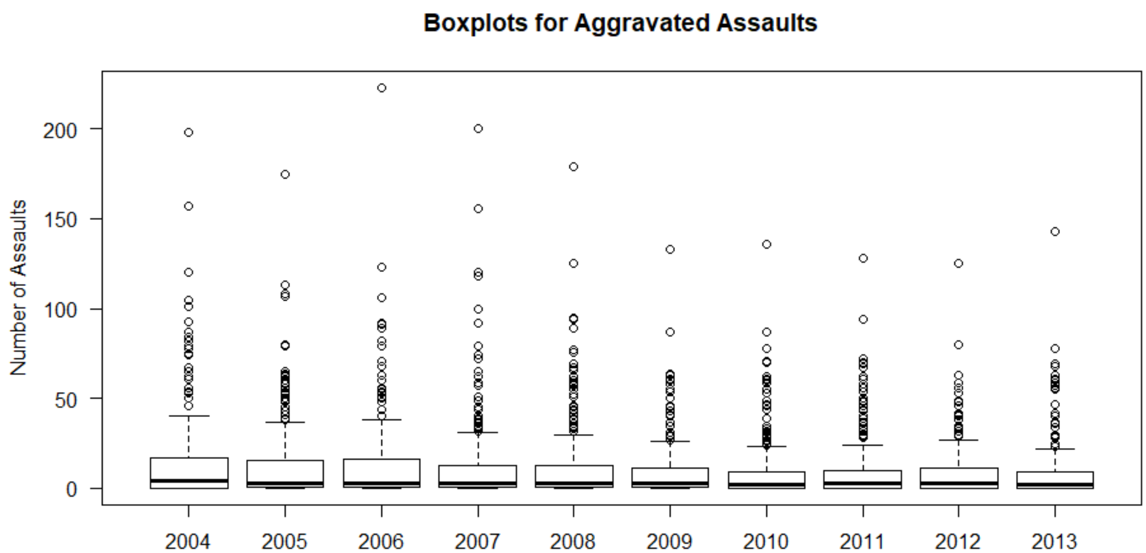

Figure 10a. Atlanta box plots for aggravated assaults by neighborhood area.

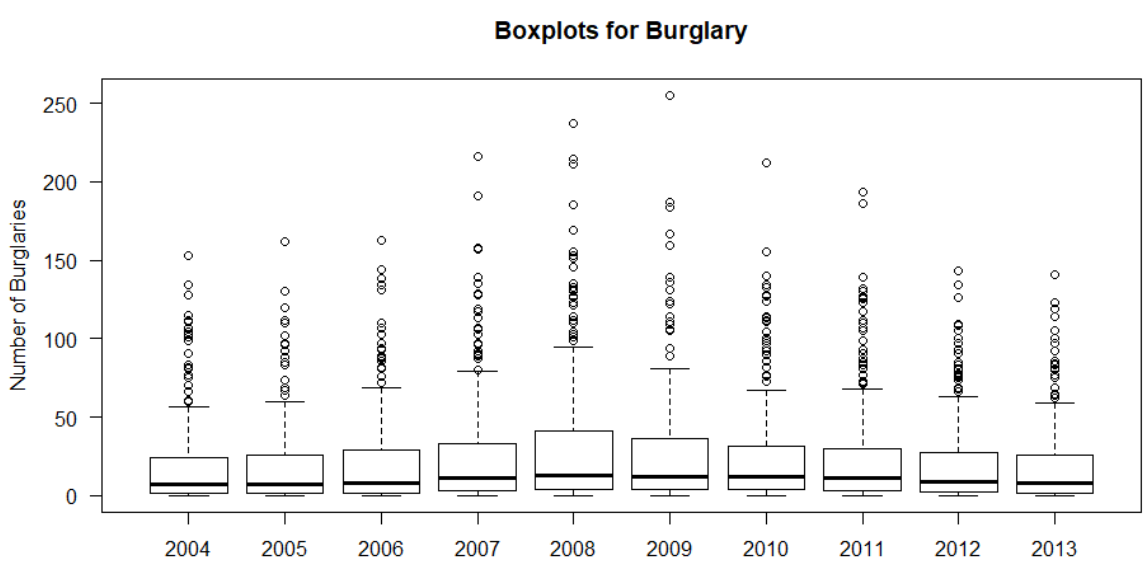

Figure 10b. Atlanta box plots for burglary by neighborhood area.

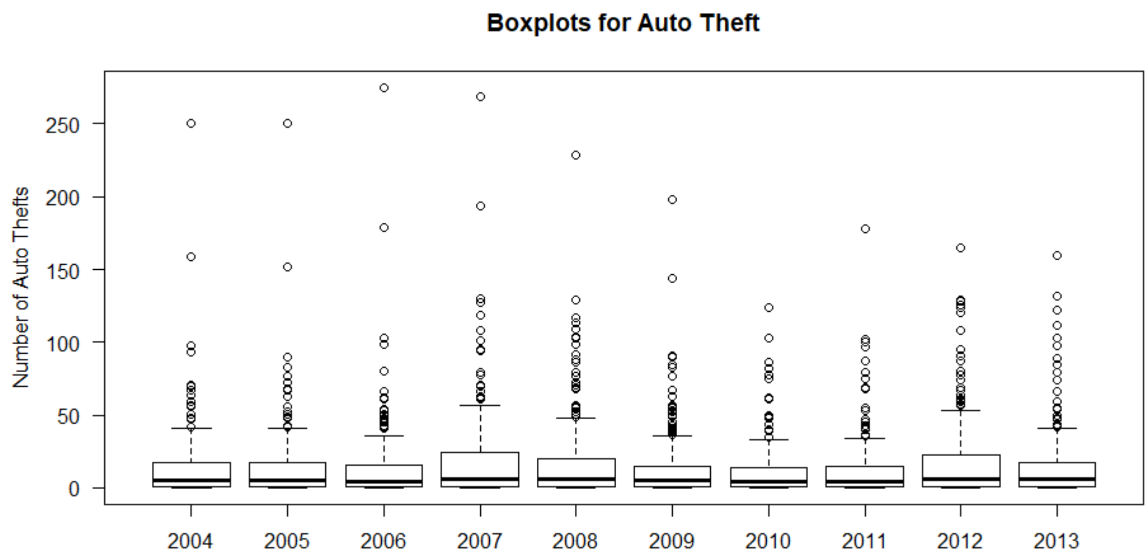

Figure 10c. Atlanta box plots for auto theft by neighborhood area.

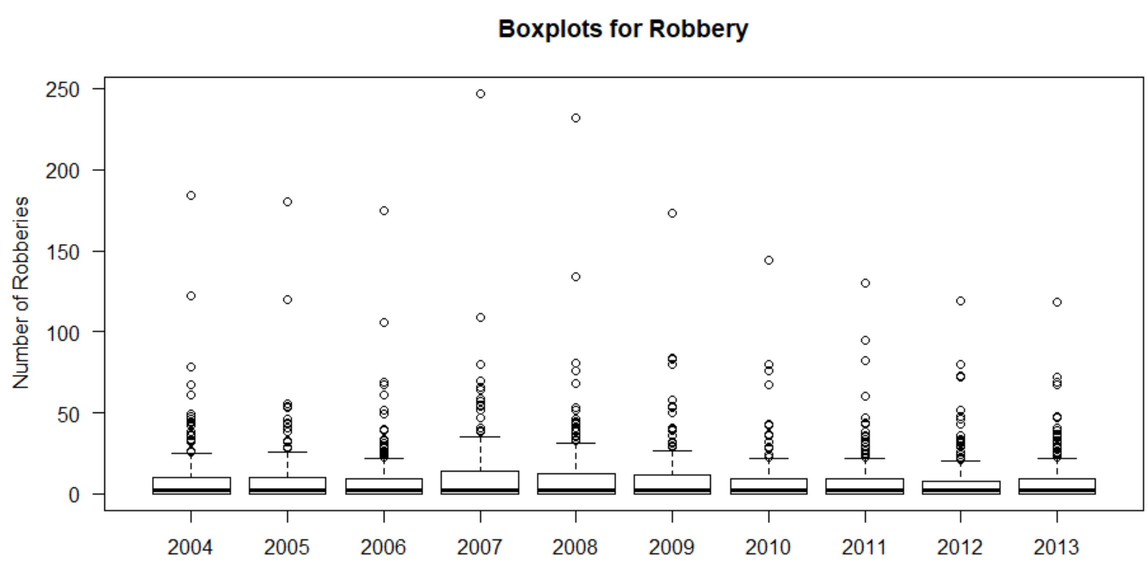

Figure 10d. Atlanta box plots for robbery by neighborhood area.

5.1.2 Seattle

In Seattle, the choropleth maps (Figures 11a-11b) show that there were four neighborhood areas that had consistently high rates of crime. Those community areas were Georgetown, Duwamish/SoDo (short for South of Downtown), Downtown Commercial Core and Pioneer Square/International District. There were two areas that experienced very little crime. Those were Madison Park to the east and Magnolia to the west of the city. The Madison Park and Magnolia neighborhood areas contain affluent neighborhoods where the mean income for working families was between $104,000 and $244,000 (Seattle Department of Planning and Development 2005).

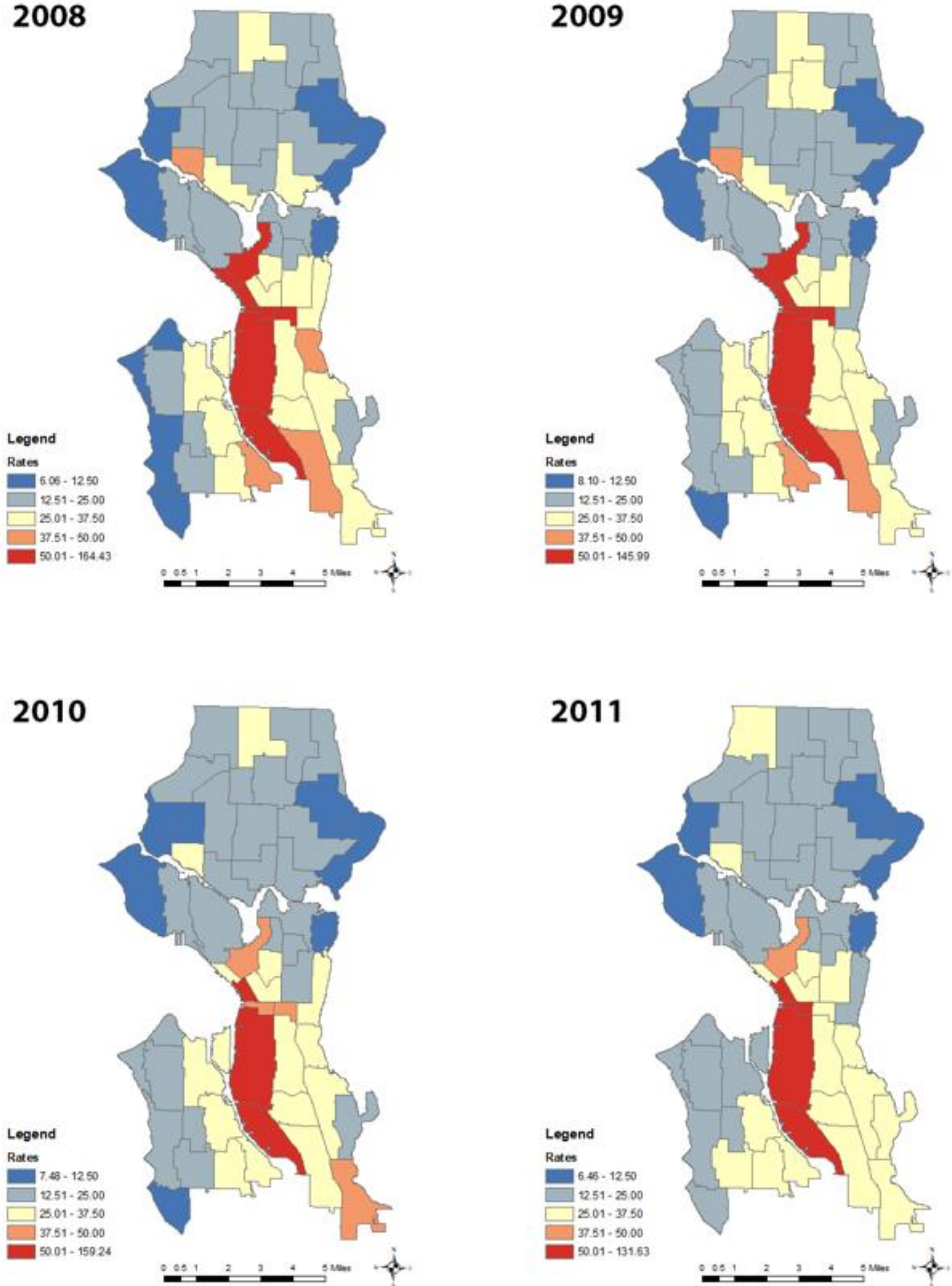

Figure 11a. Seattle crime rates per 1000 by neighborhood area, 2008-2011.

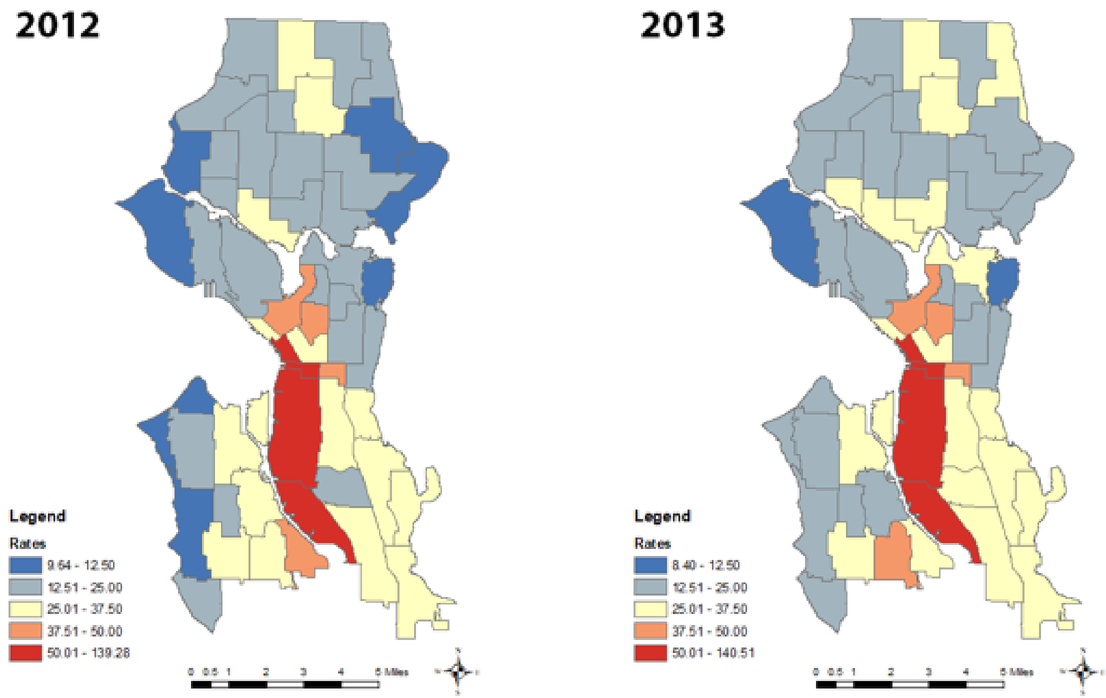

Figure 11b. Seattle crime rates per 1000 by neighborhood area, 2012-2013.

The box plots (Figures 12a-12d), like in Atlanta, reveal that property crime was generally higher, especially Burglary/Breaking and Entering. The data was also positively skewed, given the lower boundary of the data.

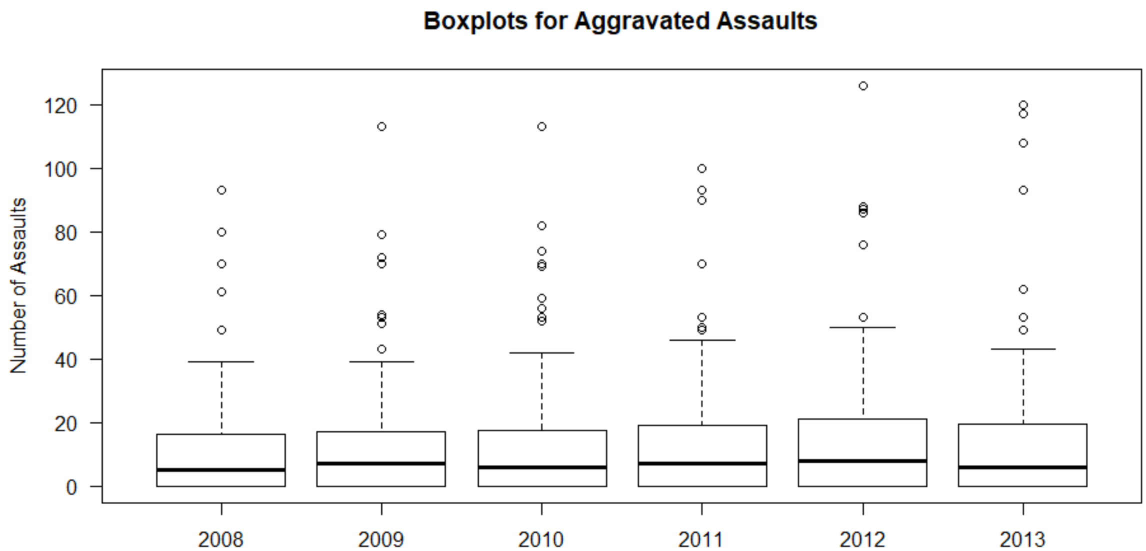

Figure 12a. Seattle box plots for aggravated assaults by neighborhood area.

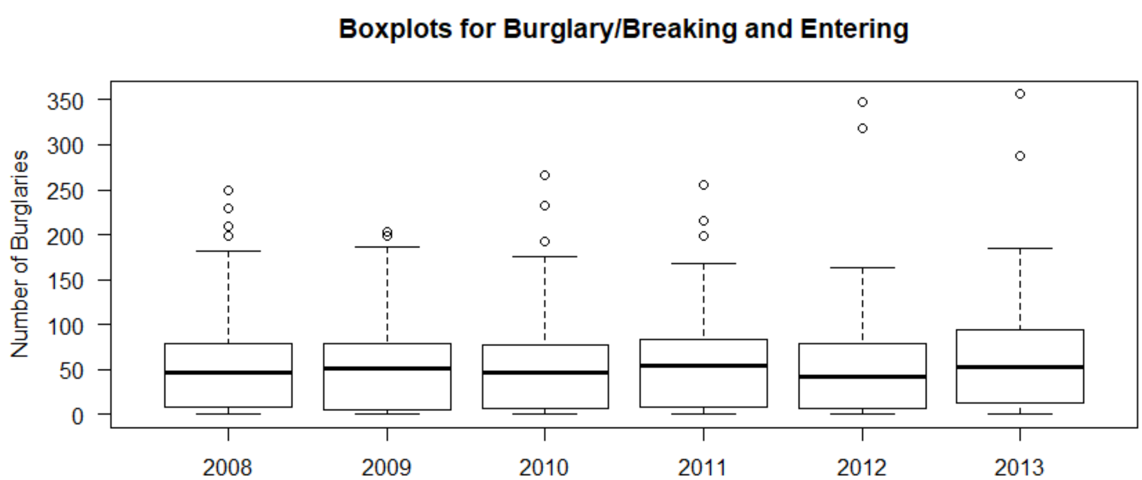

Figure 12b. Seattle box plots for burglary by neighborhood area.

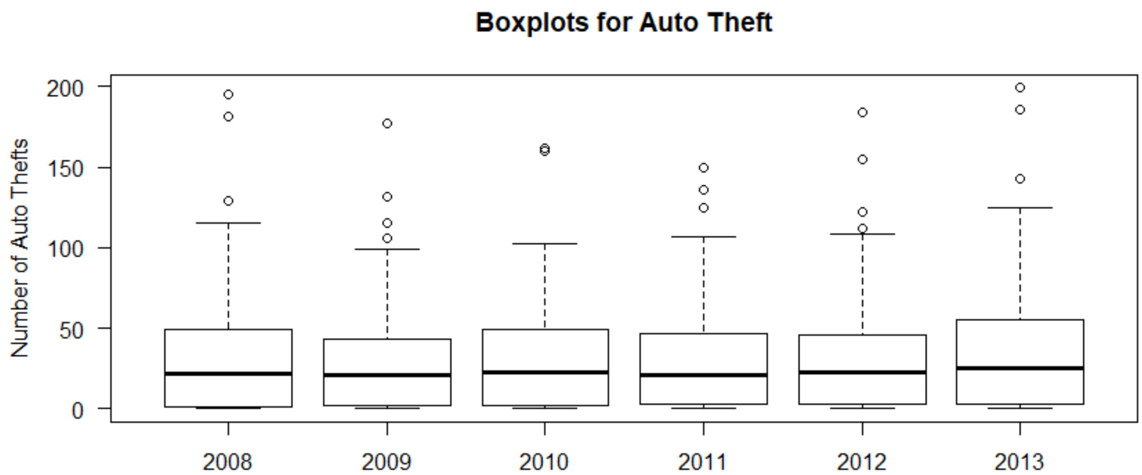

Figure 12c. Seattle box plots for auto theft by neighborhood area.

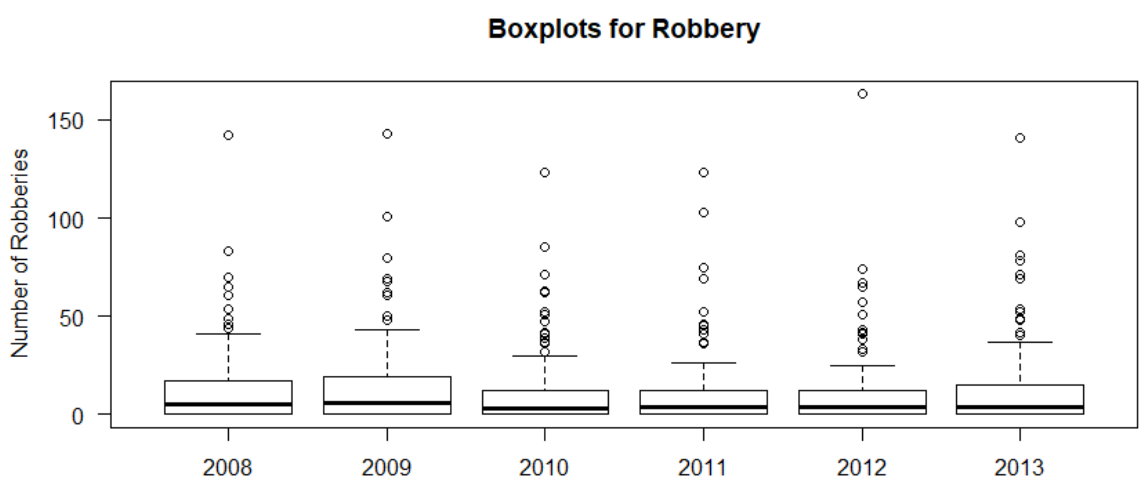

Figure 12d. Seattle box plots for robbery by neighborhood area.

5.1.3 Chicago

Choropleth maps for Chicago (Figures 13a-13c) showed there was one community area with consistently high crime rates across the 10-year period. It was Washington Park. And, through 2012, two additional community areas with consistently high rates of crime were Englewood and Greater Grand Crossing. Community areas with consistently low rates of crime were in the northwestern part of the city. They were Forest Glen, Jefferson Park, Norwood Park, and Edison Park and Dunning. While these areas were not particularly high-income neighborhoods with respect to other communities such as Lincoln Park, Near North Side and The Loop (all located on the shore of Lake Michigan and had median household incomes greater than $98,000), Forest Glen and Edison Park did have higher median household incomes between $94,000 and $96,000 (U.S. Census Bureau, 2010).

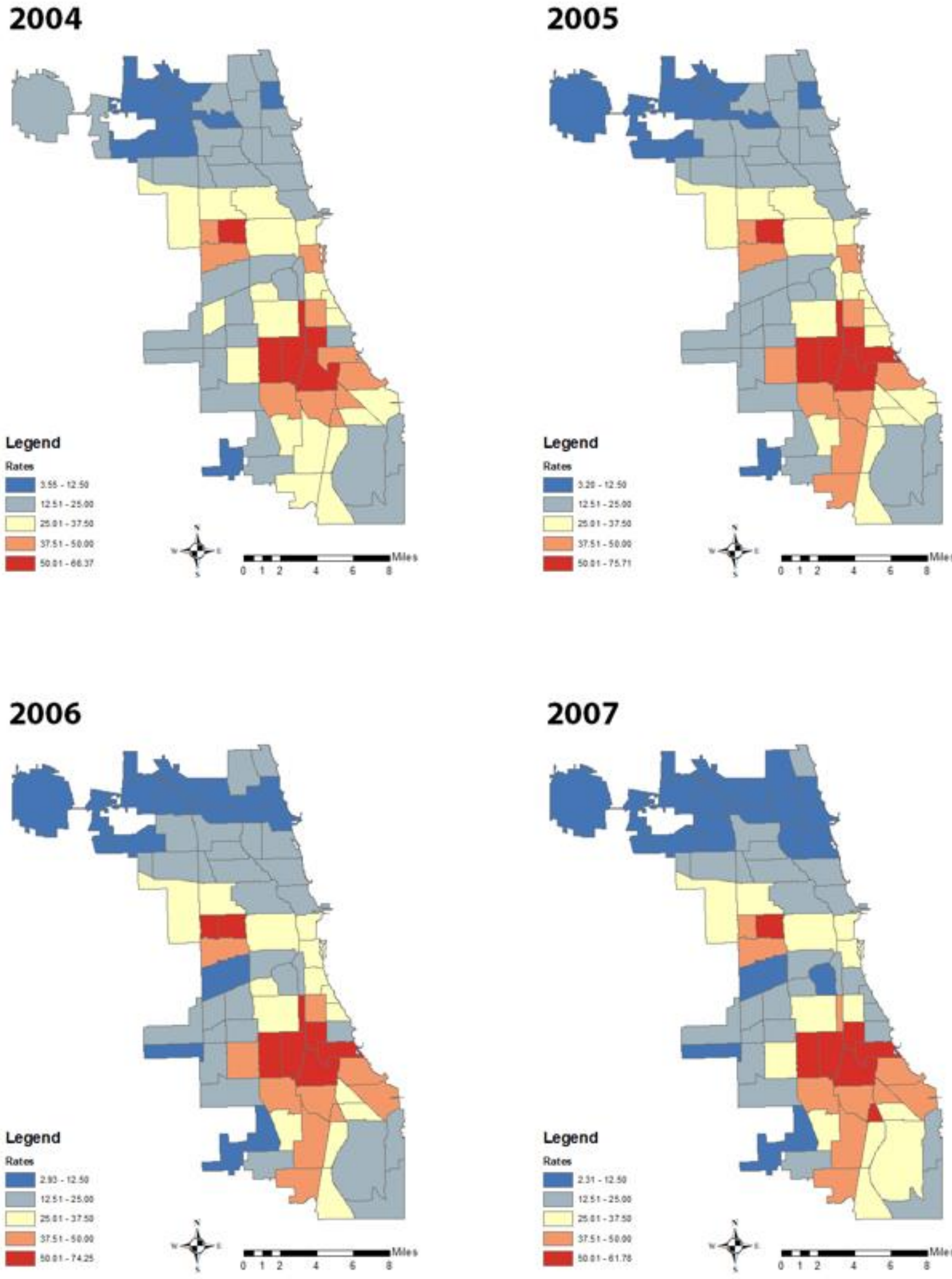

Figure 13a. Chicago crime rates per 1000 by neighborhood area, 2004-2007.

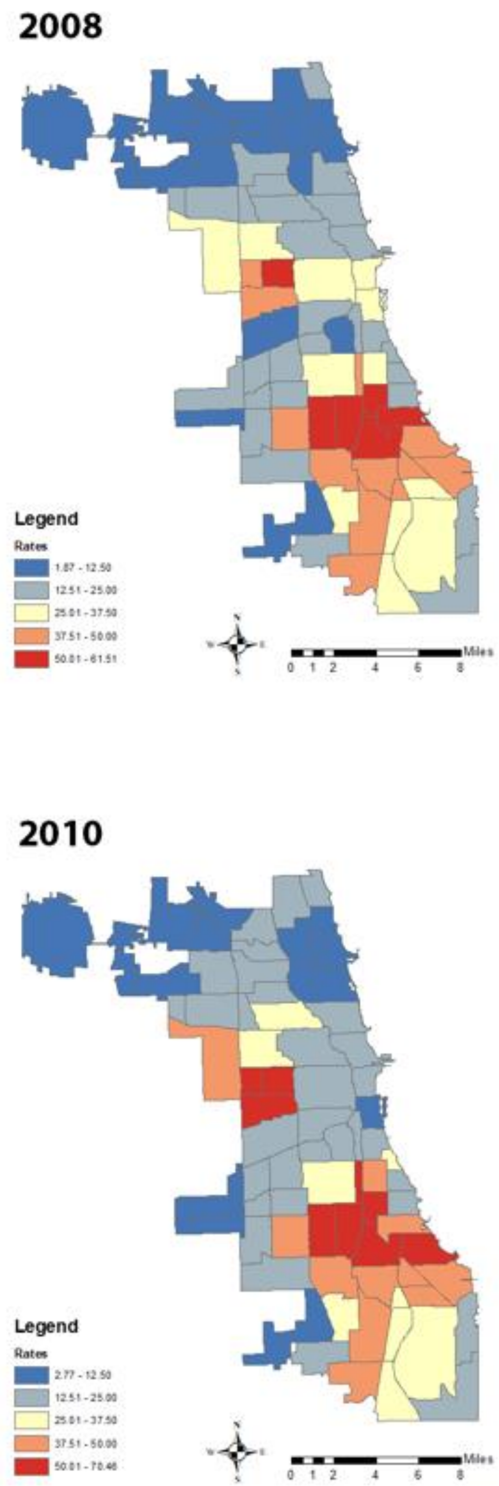

Figure 13b. Chicago crime rates per 1000 by neighborhood area, 2008-2011.

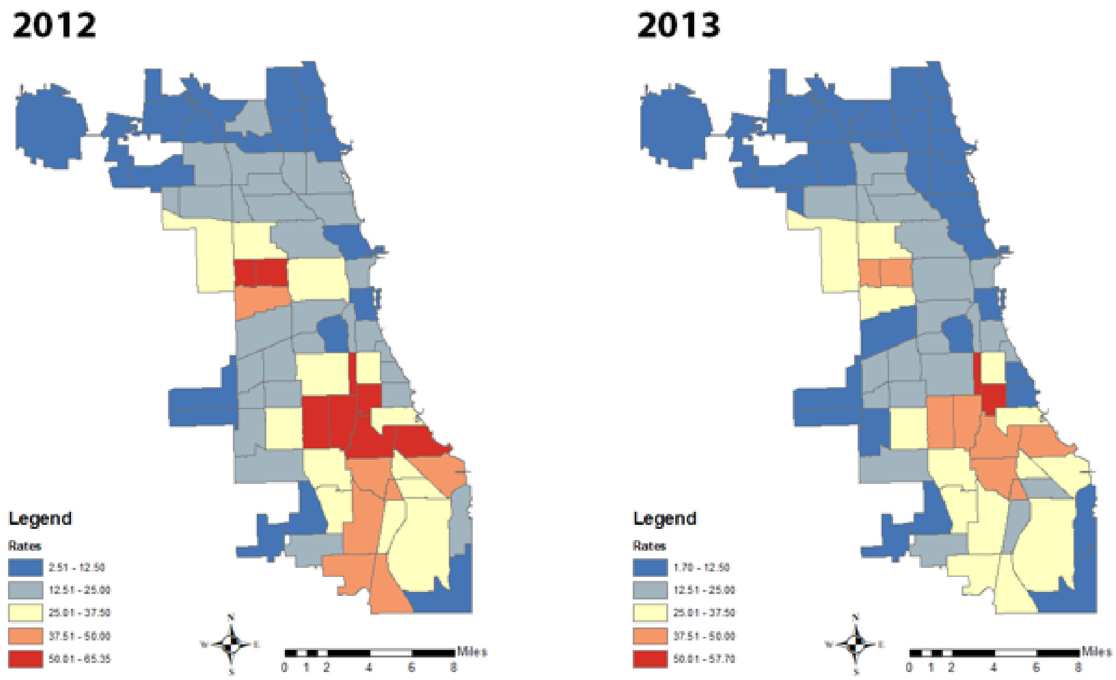

Figure 13c. Chicago crime rates per 1000 by neighborhood area, 2012-2013.

The box plots (Figures 14a-14d) show that the data are not normally distributed. They are positively skewed as with the other two cities. The median of each crime type was relatively the same, except for Burglary and Auto Theft. The median point for burglary in 2013 was visibly lower than previous years. The median point for auto theft decreased through 2009, then increased to 2011 before decreasing again. The pattern was more dramatic in the 75th percentile (the whiskers) of the box plots.

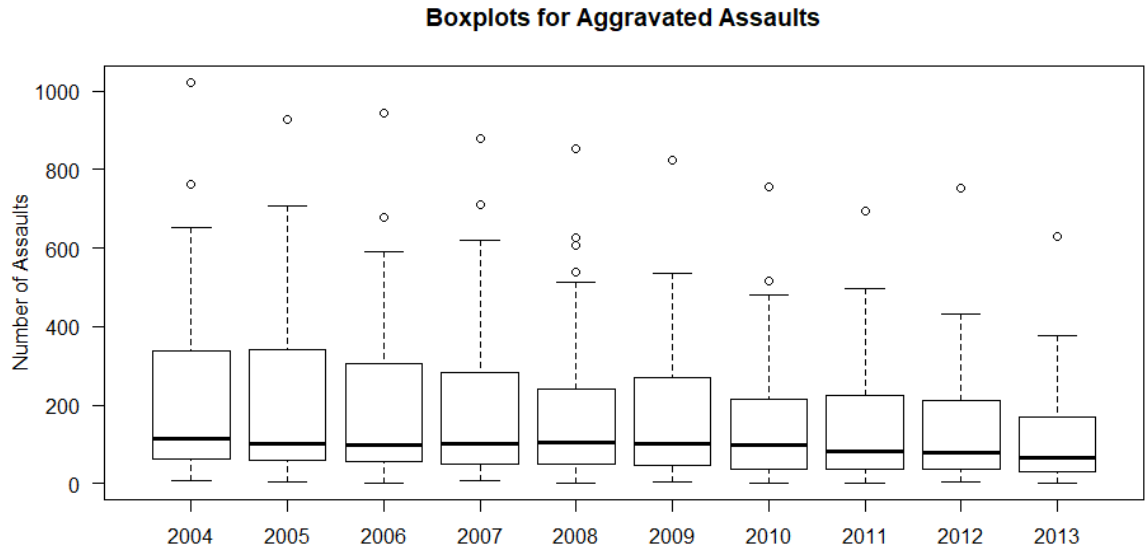

Figure 14a. Chicago box plots for aggravated assaults by neighborhood.

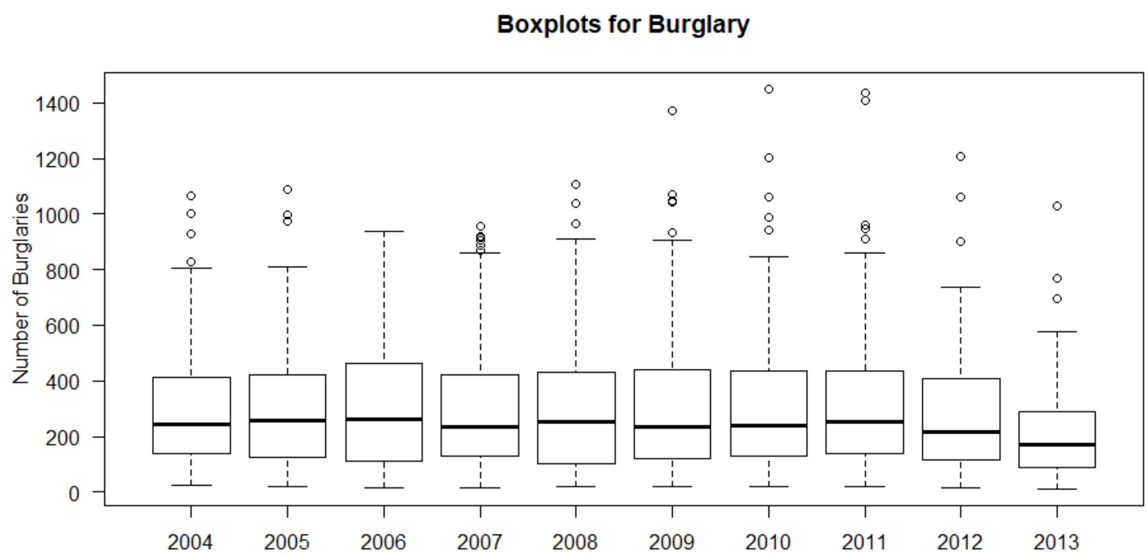

Figure 14b. Chicago box plots for burglary by neighborhood.

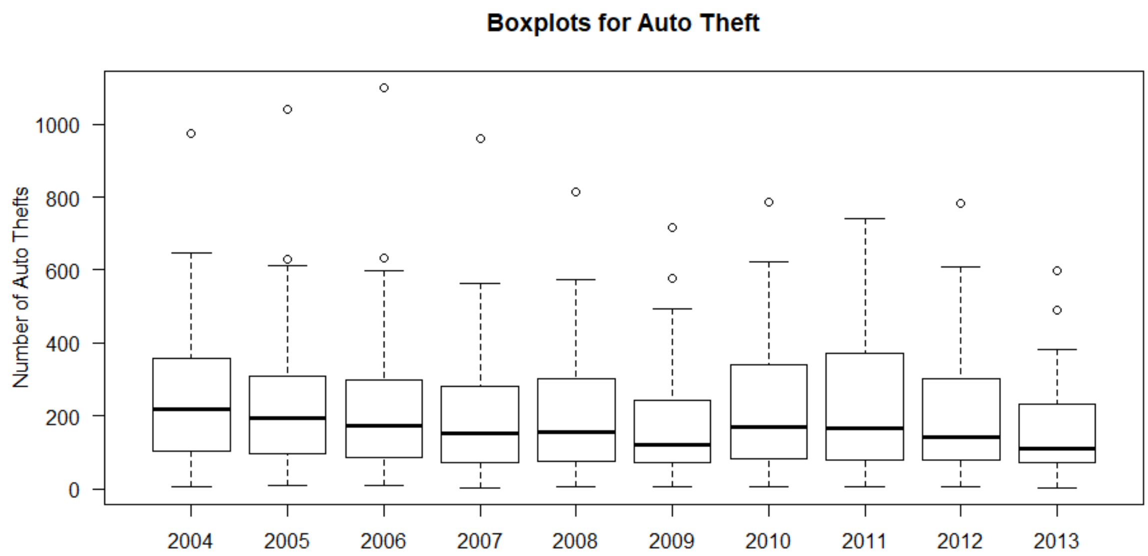

Figure 14c. Chicago box plots for auto theft by neighborhood.

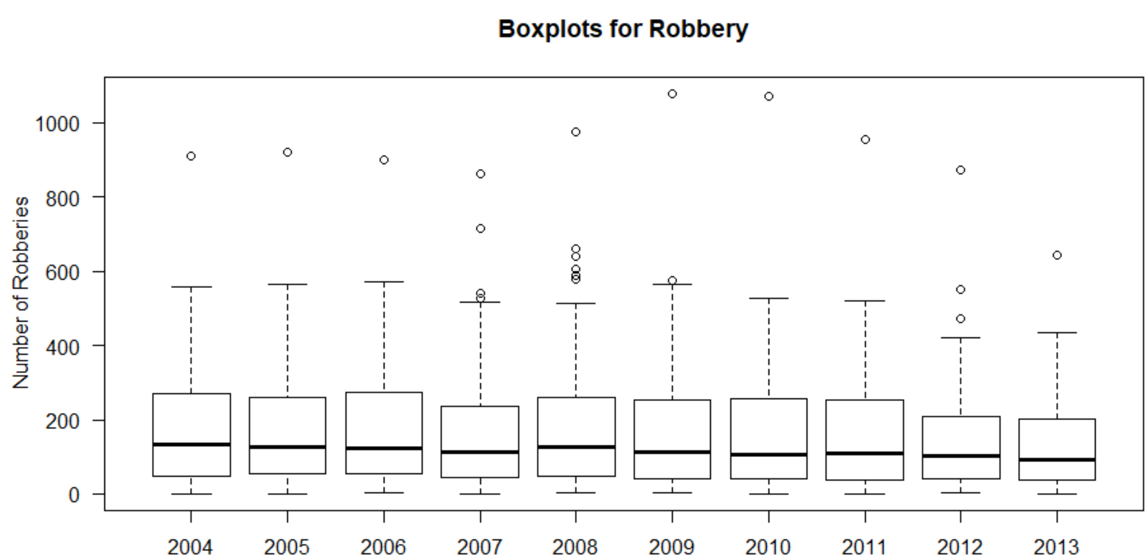

Figure 14d. Chicago box plots for robbery by neighborhood.

5.2 Ordinary Least Squares

To derive a properly specified OLS model, exploratory regression was performed to find an optimal number of correlated variables from 22 geographic and demographic factors (Table 2). While the demographic variables were spatially dependent, they did not contain the more precise latitude and longitude coordinates as the geographic variables did.

Table 2. Variables used for regression analysis for all crime types.

Demographic Variables	**Geographic Variables**
Total Housing Units	Public Housing
Total Population	Schools (including Primary Schools, Secondary Schools, and Postsecondary Institutions)
Median Age	Bars
Median Household Income	ATMs
Occupied Housing Units	Transit Stops (including bus and metro rail stops)
Owner Occupied Housing Units	Shelters
Renter Occupied Housing Units	Check Cashing Facilities
Vacant Housing Units	Places of Worship
	Night Clubs
	Police Stations
	Hospitals
	Liquor Stores
	Malls
	Rehabilitation Facilities (for substance recovery)

The exploratory regression was completed for each crime category within each city's data. Each crime category contained a different number of model attributes that were either positively or negatively correlated. The best model was chosen based on the highest Adjusted R-squared (AdjR2) value and the lowest corrected Akaike Information Criteria (AICc) value, meaning if one model had a higher AdjR2 value, but the AICc was also higher, the model was not selected. The chosen attributes were then used for OLS modeling.

5.2.1 Atlanta

The factors correlated with Aggravated Assault with a negative relationship were: Median household income and Bars. The positively correlated factors were Renter occupied housing, Transit stops, Shelters, and places of Worship (Table 3a). These explained 75.2 percent of the observed phenomenon, leaving 24.8 percent unexplained. The AICc value was 903.74 (Table 3b). Since the Koenker (BP) Statistic was significant, as indicated by the asterisk, I relied on the Robust_Pr [b] (robust probability) column to determine the significance of the coefficients. All variables were statistically significant, as indicated by the asterisk.

Table 3a. Atlanta OLS independent variables highly correlated with Aggravated Assault.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-2.974155	7.392632	-0.402313	0.688374	6.729882	-0.441933	0.659560	--------
MED_HH_INC	-0.000164	0.000096	-1.704867	0.091528	0.000082	-2.008937	0.047410*	1.650250
RENTER	0.013603	0.003384	4.019646	0.000122*	0.003408	3.991538	0.000135*	1.823827
BARS	-1.065204	0.393651	-2.705958	0.008086*	0.373895	-2.848935	0.005389*	3.097926
TRANSIT	0.444951	0.094699	4.698605	0.000010*	0.098047	4.538130	0.000018*	2.956492
SHELTERS	11.185181	4.755860	2.351873	0.020760*	4.846035	2.308110	0.023180*	1.525421
WORSHIP	3.421613	0.561061	6.098472	0.000000*	0.673073	5.083570	0.000002*	1.635313

Table 3b. Atlanta OLS diagnostics for Aggravated Assault showing model performance.

OLS Diagnostics

Input Features:	nbsta_attributes	Dependent Variable:	ASSAULT
Number of Observations:	101	Akaike's Information Criterion (AICc) [d]:	903.741031
Multiple R-Squared [d]:	0.766875	Adjusted R-Squared [d]:	0.751995
Joint F-Statistic [e]:	51.536323	Prob(>F), (6,94) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	324.885841	Prob(>chi-squared), (6) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	12.710438	Prob(>chi-squared), (6) degrees of freedom:	0.047872*
Jarque-Bera Statistic [g]:	1.097763	Prob(>chi-squared), (2) degrees of freedom:	0.577596

Checking the mapped standardized residuals (Figure 15a) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of -0.693647 (Figure 15b).

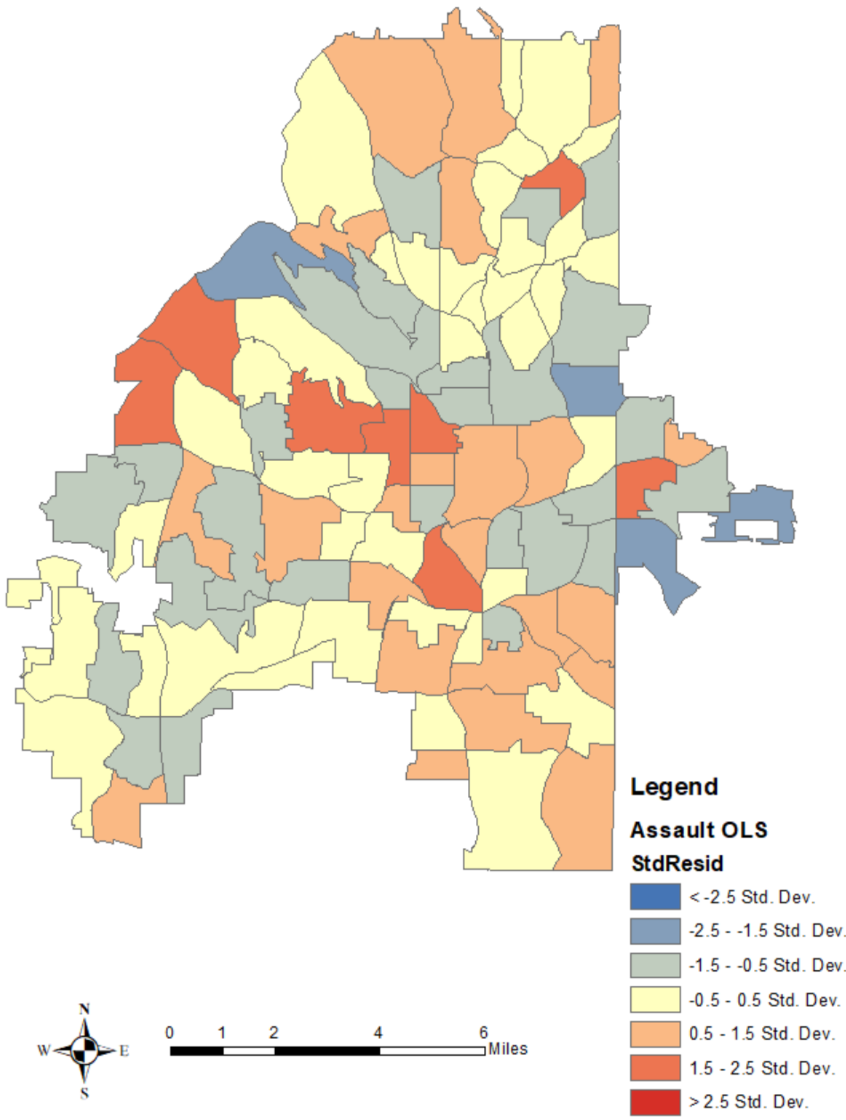

Figure 15a. Atlanta map showing OLS model standardized residuals for Aggravated Assault.

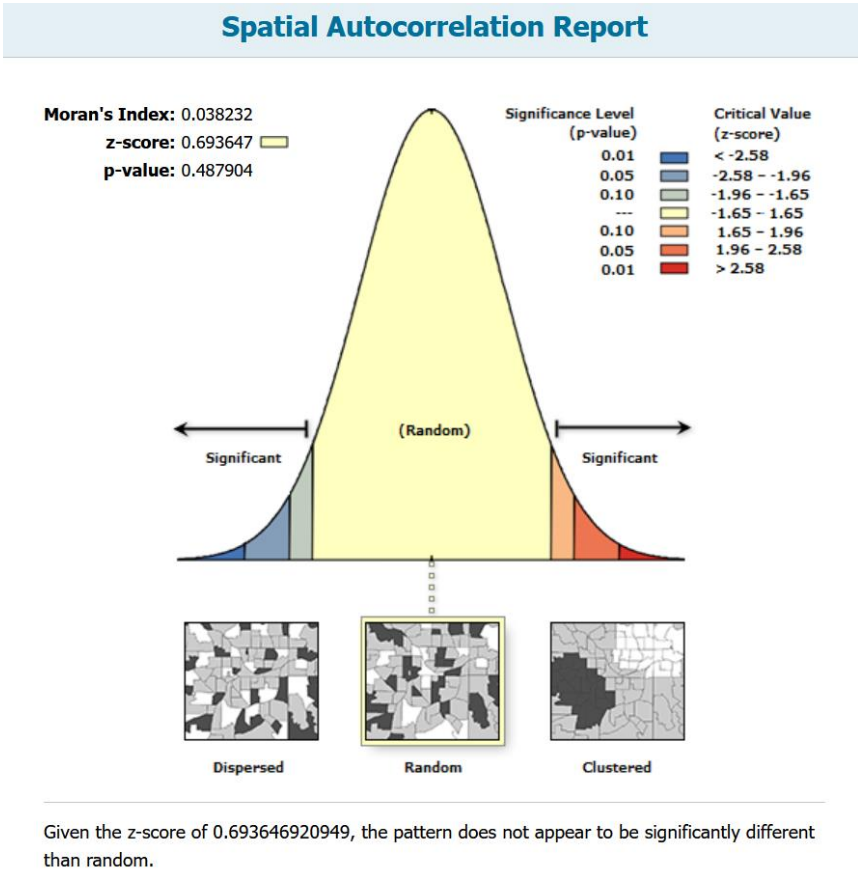

Figure 15b. Atlanta spatial autocorrelation report for Aggravated Assault showing the pattern to be random.

Factors highly correlated with Robbery with a negative relationship were: Occupied housing. The positively correlated factors were Renter occupied housing, Transit stops, Shelters, and Liquor stores (Table 3c). These explained 85.8 percent of the observed phenomenon, leaving 14.2 percent unexplained. The AICc value was 805.81 (Table 3d). Since the Koenker (BP) Statistic was significant, as indicated by the asterisk, I relied on the Robust_Pr [b] (robust probability) column to determine the significance of the coefficients. All variables were statistically significant, as indicated by the asterisk.

Table 3c. Atlanta OLS independent variables highly correlated with Robbery.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-3.884060	2.572147	-1.510046	0.134358	2.446151	-1.587825	0.115656	--------
OCCUPIED	-0.011055	0.002755	-4.013216	0.000124*	0.002761	-4.004849	0.000128*	5.346597
RENTER	0.021130	0.003765	5.612016	0.000000*	0.004430	4.769251	0.000008*	5.877307
TRANSIT	0.331530	0.059804	5.543577	0.000000*	0.071779	4.618748	0.000014*	3.069542
SHELTERS	8.173616	2.942097	2.778160	0.006587*	3.975251	2.056126	0.042510*	1.519725
LIQUOR	1.659214	0.308303	5.381765	0.000001*	0.365828	4.535505	0.000018*	3.468205

Table 3d. Atlanta OLS diagnostics for Robbery showing model performance.

OLS Diagnostics

Input Features:	nbsta_attributes	Dependent Variable:	ROBBERY
Number of Observations:	101	Akaike's Information Criterion (AICc) [d]:	805.815264
Multiple R-Squared [d]:	0.865271	Adjusted R-Squared [d]:	0.858180
Joint F-Statistic [e]:	122.024194	Prob(>F), (5,95) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	277.795066	Prob(>chi-squared), (5) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	16.719372	Prob(>chi-squared), (5) degrees of freedom:	0.005064*
Jarque-Bera Statistic [g]:	4.304248	Prob(>chi-squared), (2) degrees of freedom:	0.116237

Checking the mapped standardized residuals (Figure 15c) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of 1.57469 (Figure 15d).

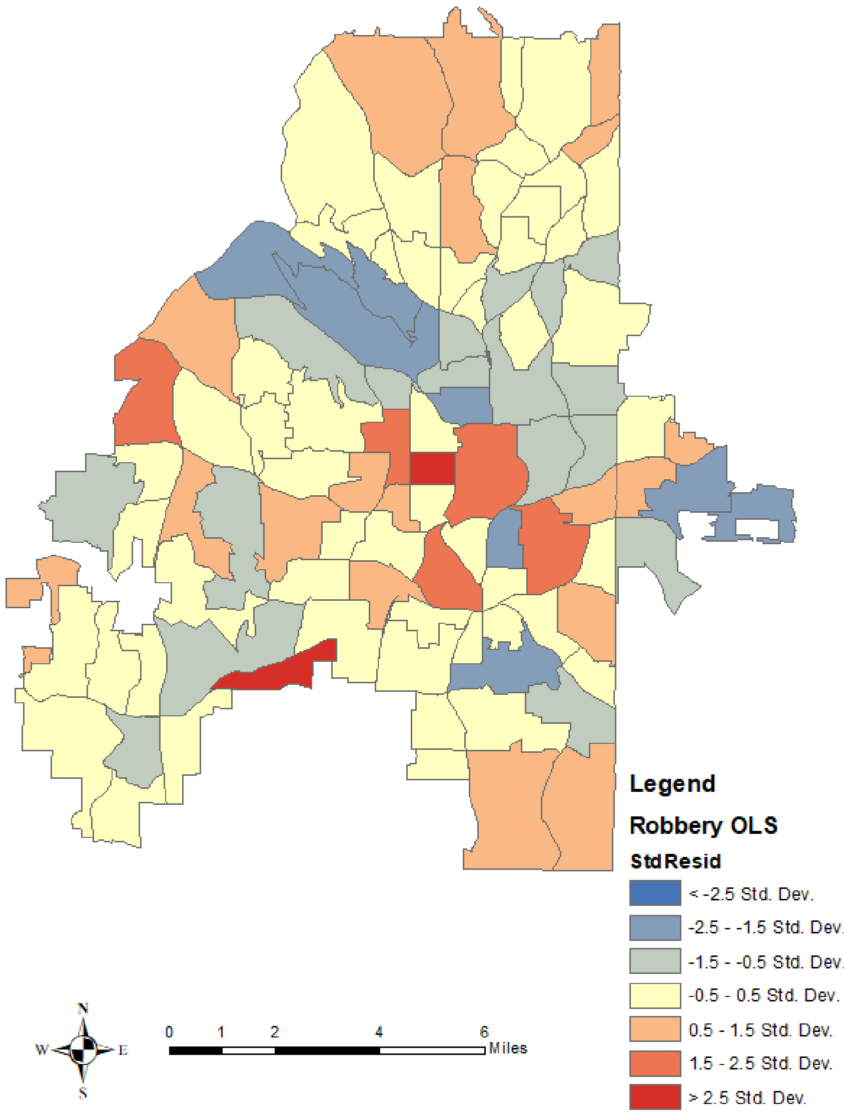

Figure 15c. Atlanta map showing OLS model standardized residuals for Robbery.

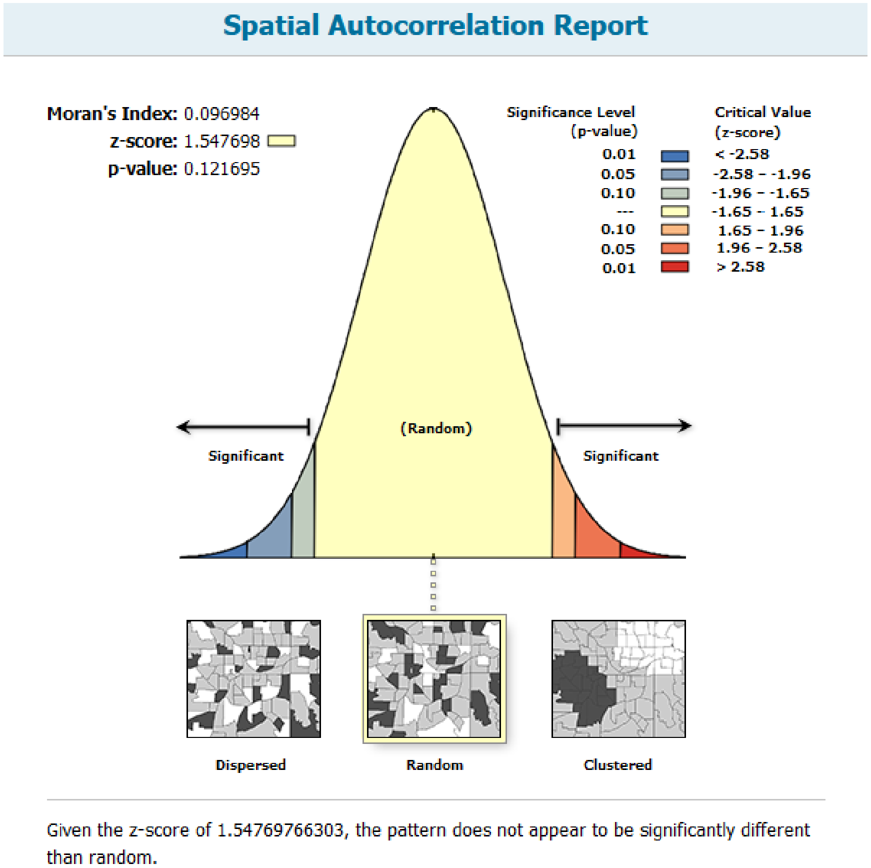

Figure 15d. Atlanta spatial autocorrelation report for Robbery showing the pattern to be random.

Highly correlated factors for Burglary with a negative relationship were: Median household income, ATMs, Check cashing facilities and Rehabilitation facilities. Positively correlated factors were: Vacant housing, Transit stops, and Liquor stores (Table 3e). These explained 73.8 percent of the observed phenomenon, leaving 26.2 percent unexplained. The AICc value was 1002.92 (Table 3f). All variables were statistically significant, as indicated by the asterisk in the Probability [b] column.

Table 3e. Atlanta OLS independent variables highly correlated with Burglary.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	51.102763	10.441051	4.894408	0.000005*	10.114059	5.052646	0.000003*	--------
MED_HH_INC	-0.000524	0.000148	-3.538115	0.000637*	0.000125	-4.190103	0.000067*	1.483266
VACANT	0.073529	0.023706	3.101708	0.002552*	0.025439	2.890455	0.004789*	1.822072
ATMS	-3.805194	0.538792	-7.062451	0.000000*	0.570103	-6.674575	0.000000*	3.773691
TRANSIT	0.790091	0.172682	4.575423	0.000016*	0.186121	4.245036	0.000055*	3.730947
CHK_CASH	-18.869495	7.024284	-2.686323	0.008554*	7.922105	-2.381879	0.019255*	2.168380
LIQUOR	6.759549	0.920847	7.340574	0.000000*	1.024064	6.600708	0.000000*	4.510689
REHAB	-23.355893	6.193522	-3.771019	0.000291*	6.801783	-3.433790	0.000897*	2.364235

Table 3f. Atlanta OLS diagnostics for Burglary showing model performance.

OLS Diagnostics

Input Features:	nbsta_attributes	Dependent Variable:	BURGLARY
Number of Observations:	101	Akaike's Information Criterion (AICc) [d]:	1002.926597
Multiple R-Squared [d]:	0.756555	Adjusted R-Squared [d]:	0.738231
Joint F-Statistic [e]:	41.288103	Prob(>F), (7,93) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	376.699577	Prob(>chi-squared), (7) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	12.183741	Prob(>chi-squared), (7) degrees of freedom:	0.094676
Jarque-Bera Statistic [g]:	0.559422	Prob(>chi-squared), (2) degrees of freedom:	0.756002

Checking the mapped standardized residuals (Figure 15e) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of 1.52841 (Figure 15f).

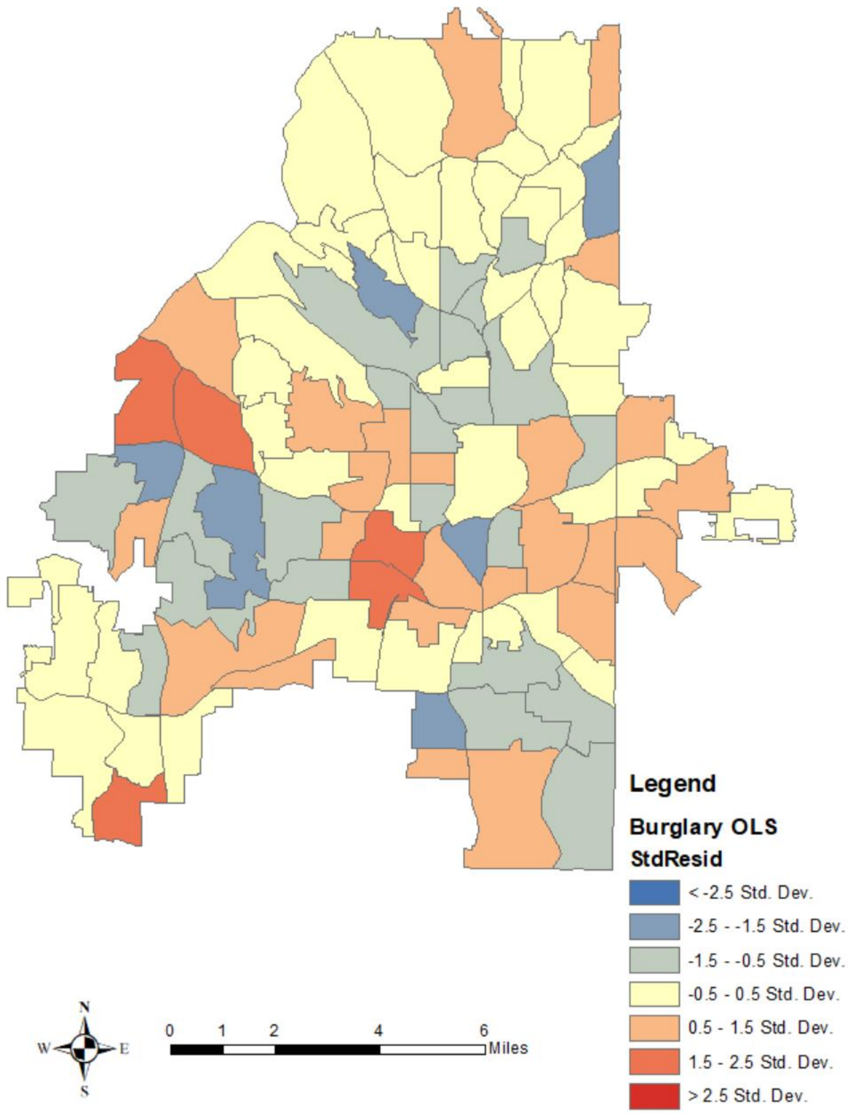

Figure 15e. Atlanta map showing OLS model standardized residuals for Burglary.

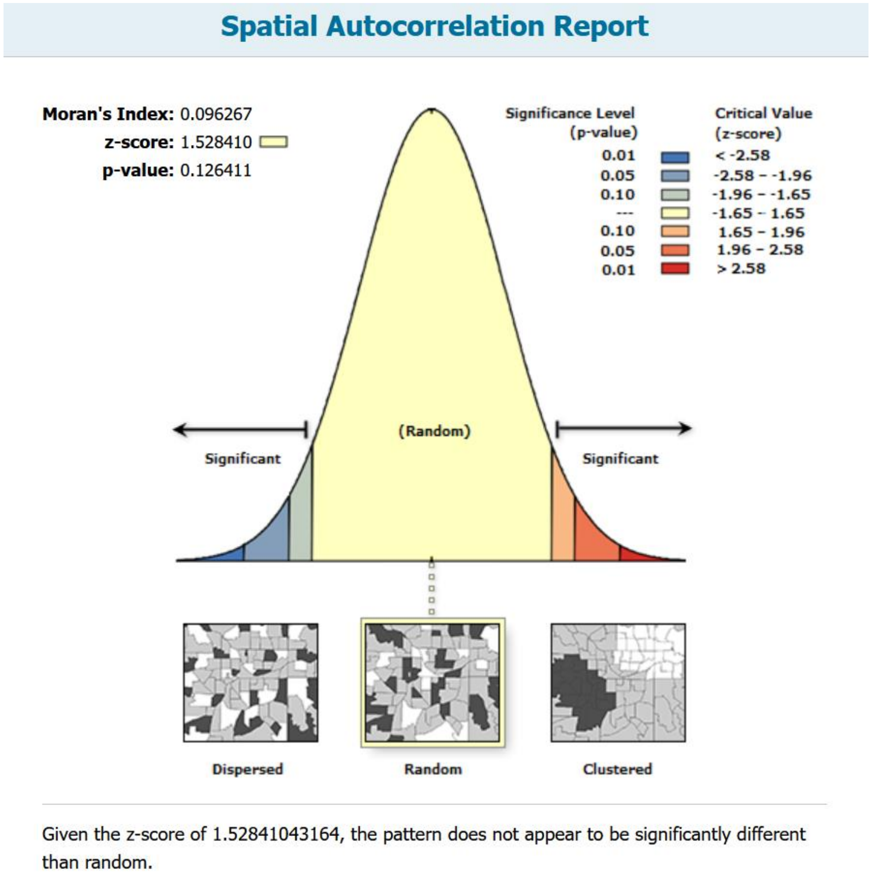

Figure 15f. Atlanta spatial autocorrelation report for Burglary showing the pattern to be random.

The factors highly correlated with Auto Theft with a negative relationship were: Median Household Income. Positively correlated factors were: Occupied housing, Schools, Transit stops, Check cashing facilities and Malls (Figure 3g). These factors explained 81.7 percent of the phenomenon, leaving 18.3 percent unexplained. The AICc value was 921.67 (Table 3h). All variables were statistically significant, as indicated by the asterisk in the Probability [b] column.

Table 3g. Atlanta OLS independent variables highly correlated with Auto Theft.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	7.802623	6.405666	1.218082	0.226242	6.290255	1.240430	0.217905	--------
MED_HH_INC	-0.000372	0.000097	-3.844365	0.000225*	0.000082	-4.509450	0.000021*	1.392477
OCCUPIED	0.012196	0.002509	4.861178	0.000005*	0.002381	5.121267	0.000002*	1.426498
SCHOOLS	6.587215	2.220603	2.966408	0.003822*	2.085036	3.159281	0.002133*	1.196114
TRANSIT	0.475633	0.102992	4.618139	0.000014*	0.138891	3.424512	0.000921*	2.928223
CHK_CASH	13.856552	4.376267	3.166295	0.002087*	6.017138	2.302848	0.023487*	1.856976
MALLS	2.627724	1.138831	2.307387	0.023222*	1.318978	1.992242	0.049244*	1.264137

Table 3h. Atlanta OLS diagnostics for Auto Theft showing model performance.

OLS Diagnostics

Input Features:	nbsta_attributes	Dependent Variable:	AUTOTHEFT
Number of Observations:	101	Akaike's Information Criterion (AICc) [d]:	921.670336
Multiple R-Squared [d]:	0.786100	Adjusted R-Squared [d]:	0.772447
Joint F-Statistic [e]:	57.576317	Prob(>F), (6,94) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	418.119043	Prob(>chi-squared), (6) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	7.629302	Prob(>chi-squared), (6) degrees of freedom:	0.266538
Jarque-Bera Statistic [g]:	0.093454	Prob(>chi-squared), (2) degrees of freedom:	0.954348

Checking the mapped standardized residuals (Figure 15g) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of 1.13505 (Figure 15h).

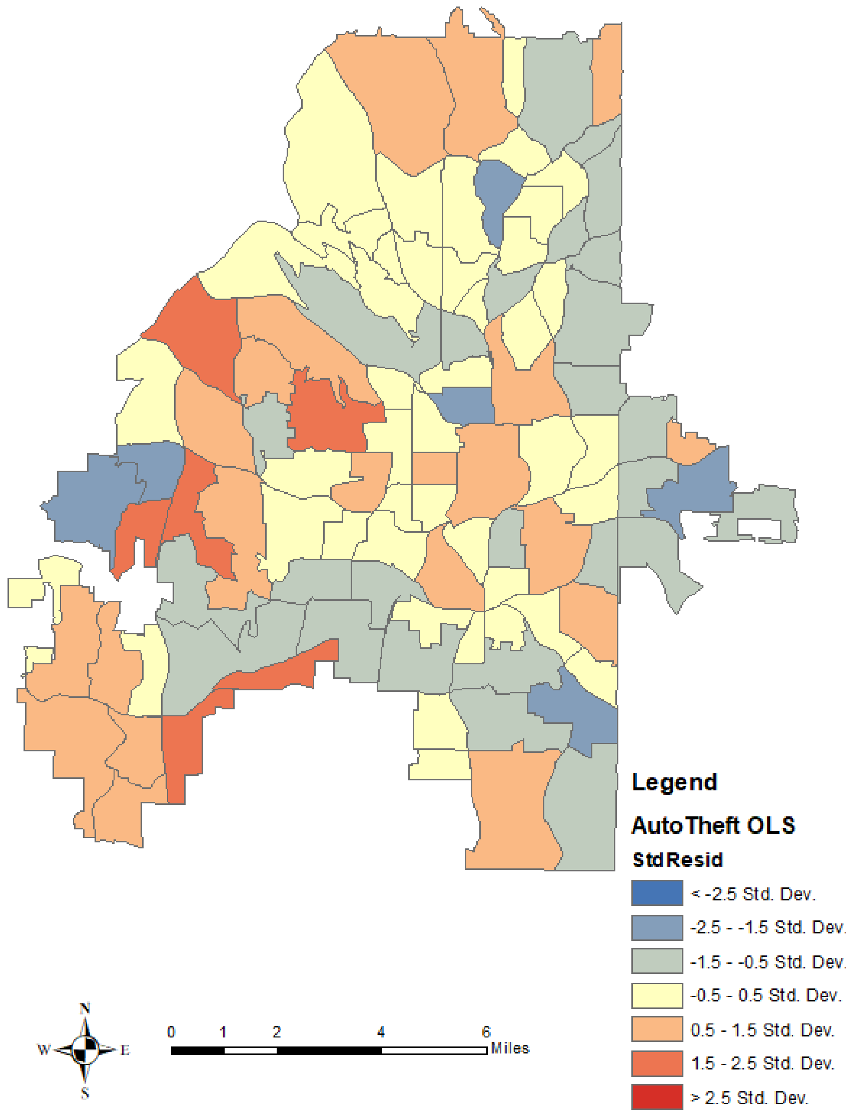

Figure 15g. Atlanta map showing OLS model standardized residuals for Auto Theft.

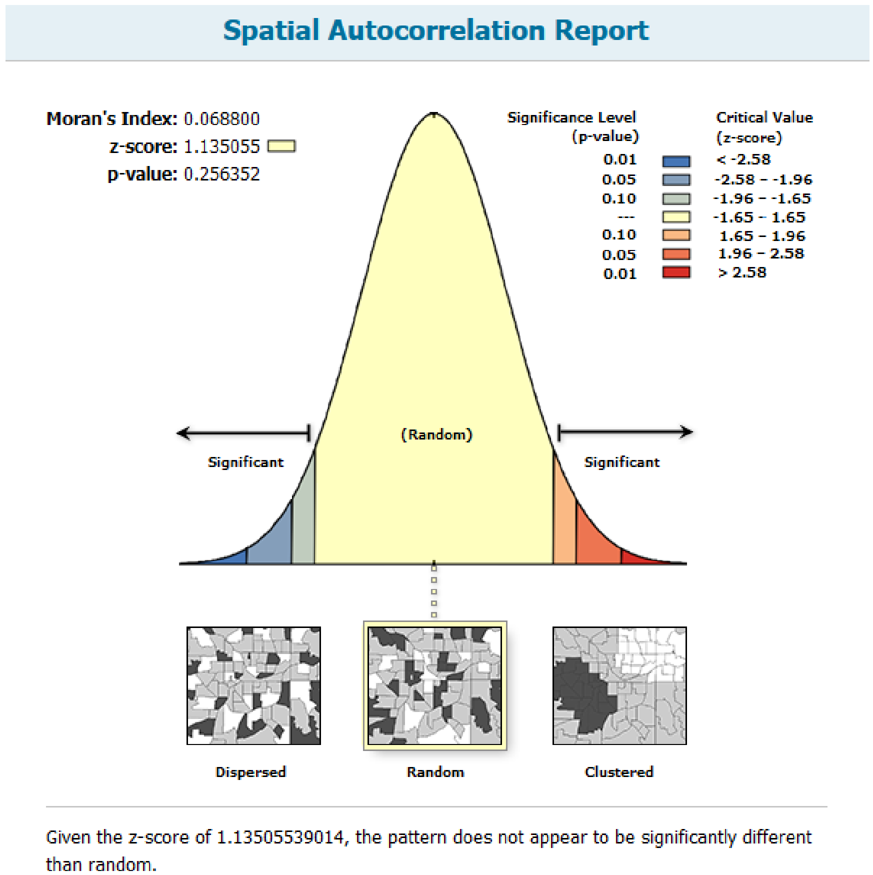

Figure 15h. Atlanta spatial autocorrelation report for Auto Theft showing the pattern to be random.

The consistent factor across the four crime types was Transit stops, which was positively correlated (Table 3i). Median household income was negatively correlated with three of the crime types, but not all four.

Table 3i: Atlanta OLS model variables used for each crime type (bold = similarities, *italics* = positive relationship).

Assault	Burglary	Auto Theft	Robbery
median household income	median household income	median household income	occupied housing
renter occupied housing	*vacant housing*	*occupied housing*	*renter occupied housing*
bars	atms	*schools*	***transit stops***
transit stops	***transit stops***	***transit stops***	*shelters*
shelters	check cashing facilities	*check cashing facilities*	*liquor stores*
places of worship	*liquor stores*	*malls*	
	rehabilitation facilities		

5.2.2 Seattle

The factors highly correlated with Aggravated Assault with a negative relationship were: Median household income and Total population. The positively correlated factors were Transit stops, Shelters, Check cashing facilities, places of Worship, Clubs and Police stations (Table 4a). These explained 85.6 percent of the observed phenomenon, leaving 14.4 percent unexplained. The AICc value was 424.03 (Table 4b). All variables were statistically significant, as indicated by the asterisk in the Probability [b] column.

Table 4a. Seattle OLS independent variables highly correlated with Aggravated Assault.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	37.755413	8.098038	4.662291	0.000029*	9.349741	4.038124	0.000213*	--------
MED_HH_INC	-0.000662	0.000152	-4.349148	0.000080*	0.000153	-4.330127	0.000085*	1.708800
TRANSIT	0.079717	0.019496	4.088924	0.000182*	0.015772	5.054479	0.000008*	1.971263
SHELTERS	5.789043	1.930506	2.998718	0.004449*	2.188251	2.645511	0.011270*	1.793032
CHKCASH	12.605682	4.151897	3.036126	0.004018*	3.842797	3.280340	0.002034*	1.249504
WORSHIP	0.806278	0.224899	3.585071	0.000840*	0.221450	3.640910	0.000712*	2.483773
CLUBS	4.567632	1.137980	4.013809	0.000229*	1.068782	4.273680	0.000102*	1.357520
POLSTA	19.072551	5.550707	3.436058	0.001300*	5.983396	3.187579	0.002642*	1.254546
POP	-0.001042	0.000445	-2.343090	0.023710*	0.000472	-2.205523	0.032688*	3.080986

Table 4b. Seattle OLS diagnostics for Aggravated Assault showing model performance.

OLS Diagnostics

Input Features:	nbcra_crimes_attributes	Dependent Variable:	ASSAULT
Number of Observations:	53	Akaike's Information Criterion (AICc) [d]:	424.034840
Multiple R-Squared [d]:	0.878900	Adjusted R-Squared [d]:	0.856882
Joint F-Statistic [e]:	39.916965	Prob(>F), (8,44) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	762.333209	Prob(>chi-squared), (8) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	7.012153	Prob(>chi-squared), (8) degrees of freedom:	0.535322
Jarque-Bera Statistic [g]:	3.659130	Prob(>chi-squared), (2) degrees of freedom:	0.160483

Checking the mapped standardized residuals (Figure 16a) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of 0.52811 (Figure 16b).

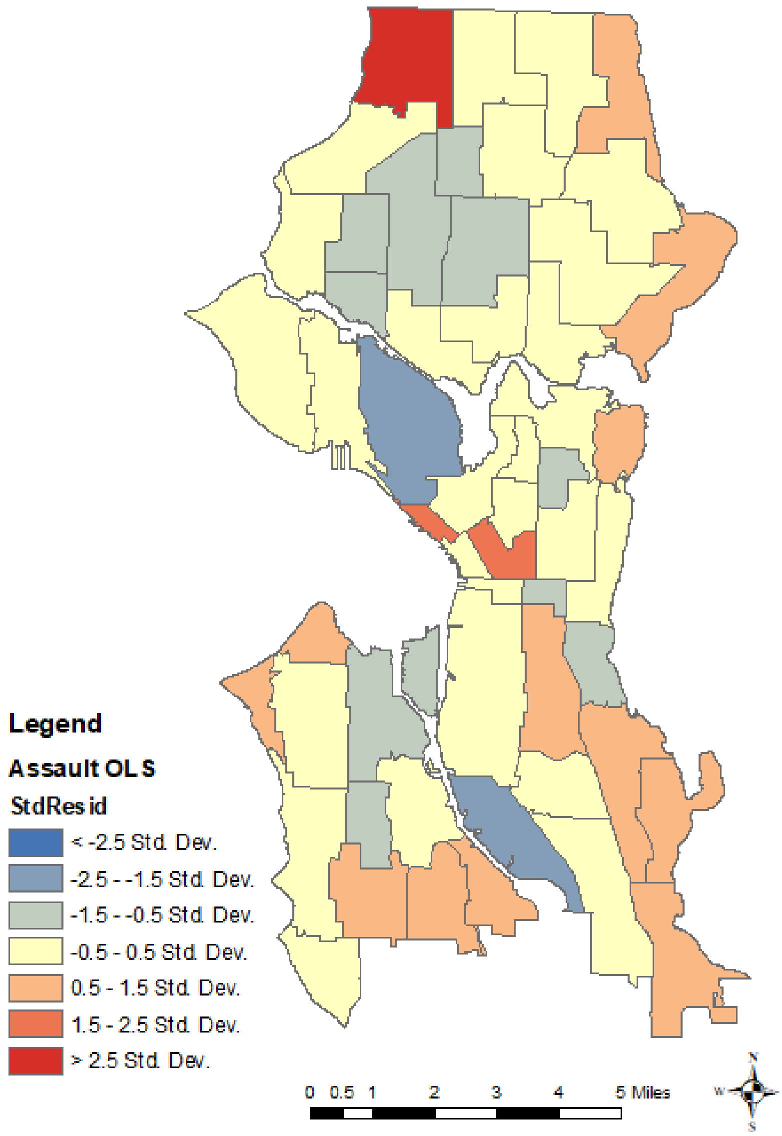

Figure 16a. Seattle map showing OLS model standardized residuals for Aggravated Assault.

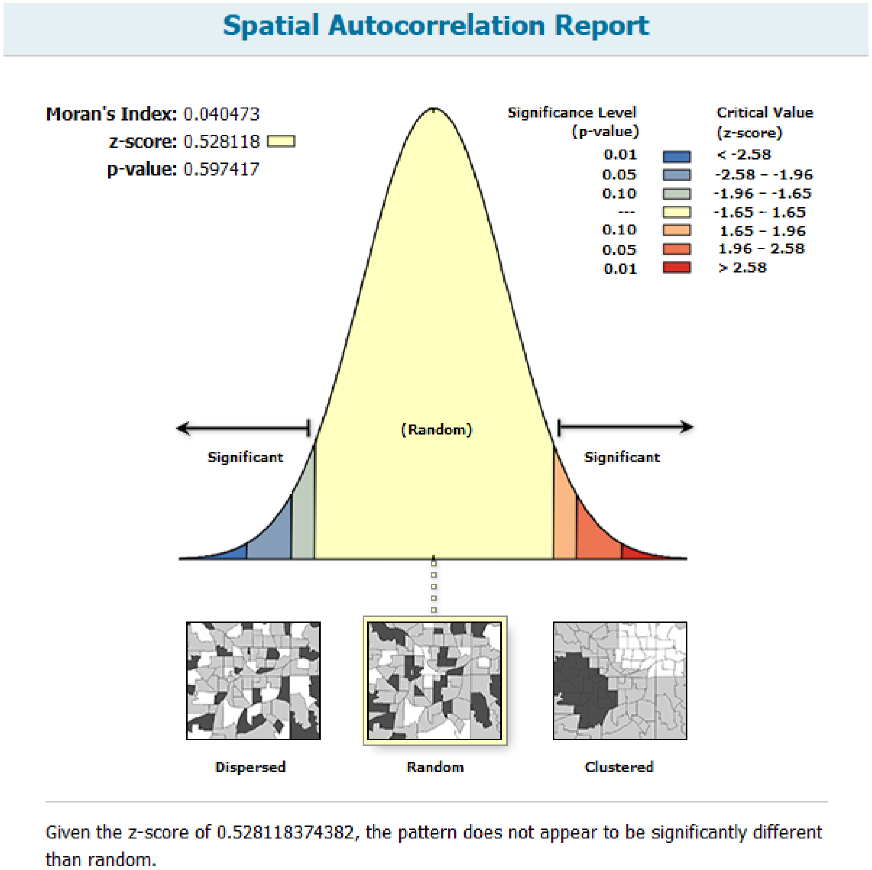

Figure 16b. Seattle spatial autocorrelation report for Aggravated Assault showing the pattern to be random.

Factors highly correlated with Robbery with a negative relationship were: Median household income. The positively correlated factors were Renter occupied housing, Hospitals, Transit stops, Shelters, Check cashing facilities, places of Worship, Clubs and Malls (Table 4c). These explained 85.1 percent of the observed phenomenon, leaving 14.9 percent unexplained. The AICc value was 440.20 (Table 4d). All variables were statistically significant, as indicated by the asterisk in the Probability [b] column.

Table 4c. Seattle OLS independent variables highly correlated with Robbery.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	46.344714	9.067007	5.111357	0.000007*	8.781578	5.277492	0.000004*	--------
MED_HH_INC	-0.000946	0.000167	-5.658596	0.000001*	0.000167	-5.678716	0.000001*	1.577253
RENTER	-0.005279	0.001270	-4.156704	0.000151*	0.001518	-3.476583	0.001175*	2.217439
HOSPITALS	16.331982	4.552954	3.587118	0.000850*	5.604669	2.913996	0.005644*	1.227481
TRANSIT	0.065515	0.022290	2.939179	0.005276*	0.017961	3.647694	0.000711*	1.971525
SHELTERS	5.299554	2.206049	2.402283	0.020684*	1.861048	2.847618	0.006729*	1.791427
CHKCASH	22.898814	4.813977	4.756735	0.000022*	5.259966	4.353415	0.000082*	1.285214
WORSHIP	1.010859	0.204204	4.950237	0.000012*	0.173528	5.825325	0.000001*	1.566712
CLUBS	4.467169	1.463527	3.052332	0.003885*	1.391662	3.209952	0.002513*	1.717914
MALLS	6.477164	2.870715	2.256289	0.029193*	2.565861	2.524362	0.015364*	1.383844

Table 4d. Seattle OLS diagnostics for Robbery showing model performance.

OLS Diagnostics

Input Features:	nbcra_crimes_attributes	Dependent Variable:	ROBBERY
Number of Observations:	53	Akaike's Information Criterion (AICc) [d]:	440.207456
Multiple R-Squared [d]:	0.877290	Adjusted R-Squared [d]:	0.851607
Joint F-Statistic [e]:	34.157794	Prob(>F), (9,43) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	371.254970	Prob(>chi-squared), (9) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	8.146706	Prob(>chi-squared), (9) degrees of freedom:	0.519432
Jarque-Bera Statistic [g]:	0.395127	Prob(>chi-squared), (2) degrees of freedom:	0.820728

Checking the mapped standardized residuals (Figure 16c) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of -0.43781 (Figure 16d).

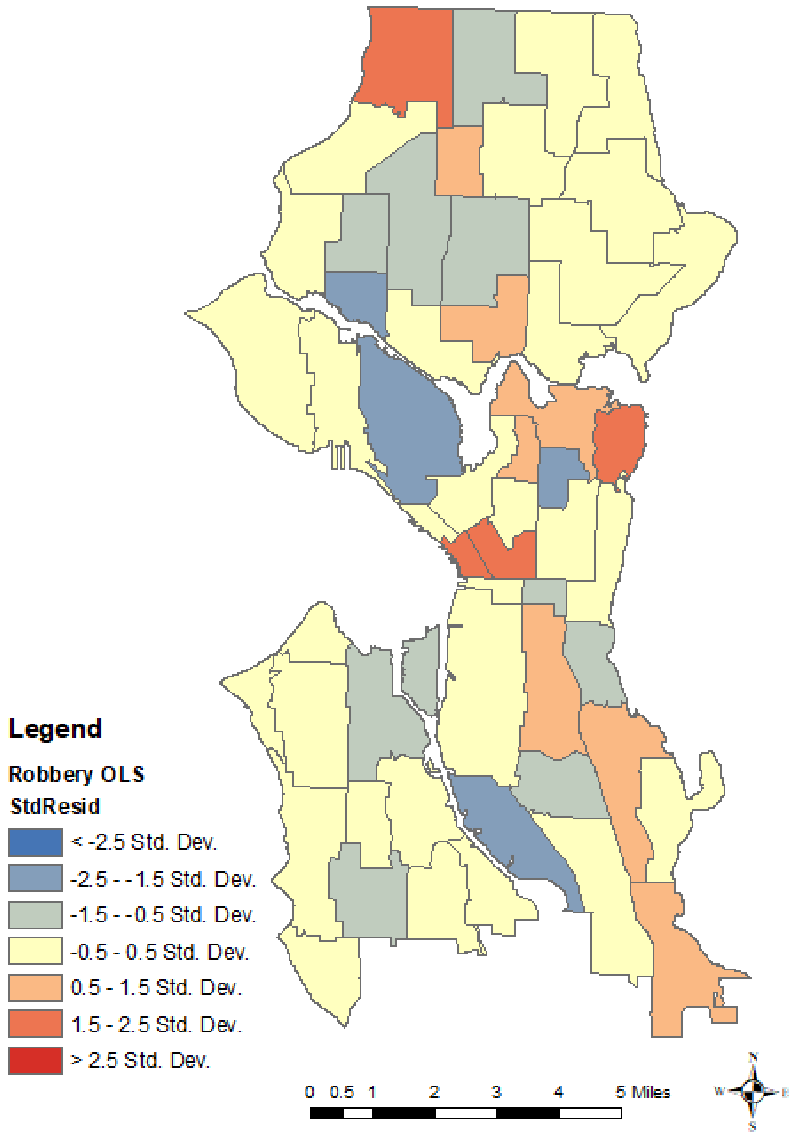

Figure 16c. Seattle map showing OLS model standardized residuals for Robbery.

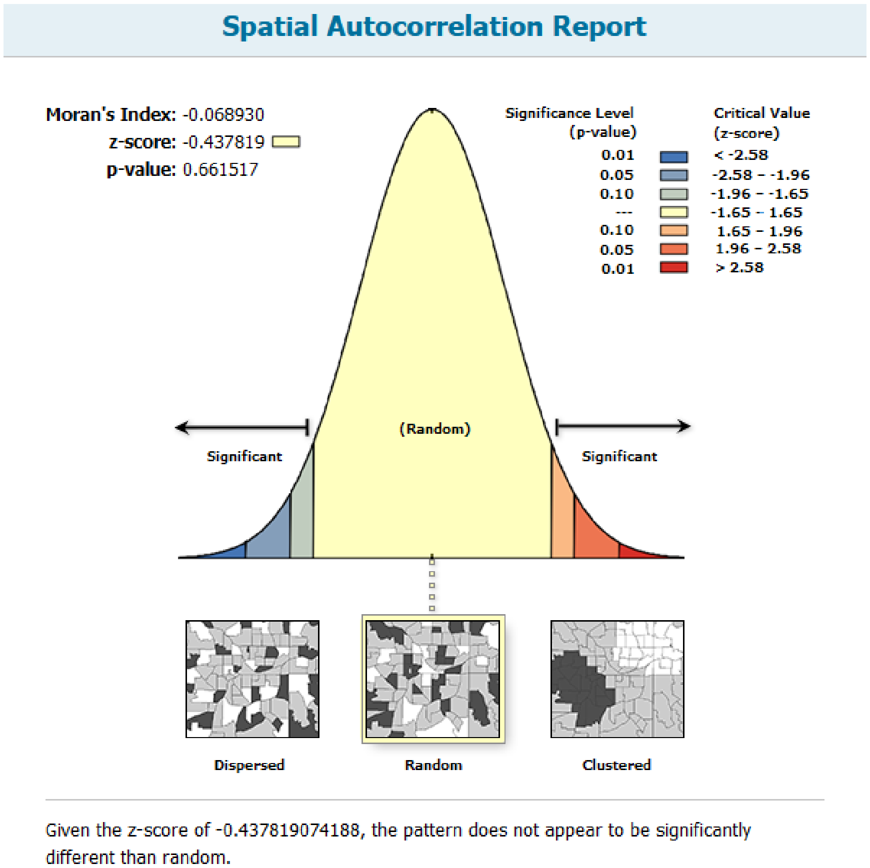

Figure 16d. Seattle spatial autocorrelation report for Robbery showing the pattern to be random.

Highly correlated factors for Burglary with a negative relationship were: Median household income and Shelters. Positively correlated factors were: Vacant housing, Transit stops, places of Worship and Total population (Figure 4e). These explained 85.5 percent of the observed phenomenon, leaving 14.5 percent unexplained. The AICc value was 528.16 (Table 4f). Since the Koenker (BP) Statistic was significant, as indicated by the asterisk, I relied on the Robust_Pr [b] (robust probability) column to determine the significance of the coefficients. All variables were statistically significant, as indicated by the asterisk.

Table 4e. Seattle OLS independent variables highly correlated with Burglary.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	48.377083	20.188865	2.396226	0.020688*	18.527960	2.611031	0.012147*	--------
MED_HH_INC	-0.001095	0.000380	-2.884520	0.005947*	0.000416	-2.635829	0.011404*	1.392420
VACANT	0.077847	0.017967	4.332693	0.000080*	0.025591	3.041915	0.003876*	2.550097
TRANSIT	0.131691	0.053594	2.457191	0.017834*	0.032623	4.036746	0.000204*	1.950955
SHELTERS	-15.065444	6.044649	-2.492361	0.016354*	6.921740	-2.176540	0.034686*	2.302224
WORSHIP	1.700513	0.618949	2.747421	0.008549*	0.816661	2.082276	0.042908*	2.463806
POP	0.005564	0.001366	4.073692	0.000181*	0.001308	4.252083	0.000103*	3.804835

Table 4f. Seattle OLS diagnostics for Burglary showing model performance.

OLS Diagnostics

Input Features:	nbcra_crimes_attributes	Dependent Variable:	BURG
Number of Observations:	53	Akaike's Information Criterion (AICc) [d]:	528.164606
Multiple R-Squared [d]:	0.872502	Adjusted R-Squared [d]:	0.855872
Joint F-Statistic [e]:	52.465210	Prob(>F), (6,46) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	590.913885	Prob(>chi-squared), (6) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	17.482722	Prob(>chi-squared), (6) degrees of freedom:	0.007664*
Jarque-Bera Statistic [g]:	0.015630	Prob(>chi-squared), (2) degrees of freedom:	0.992215

Checking the mapped standardized residuals (Figure 16e) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of 1.63365 (Figure 16f).

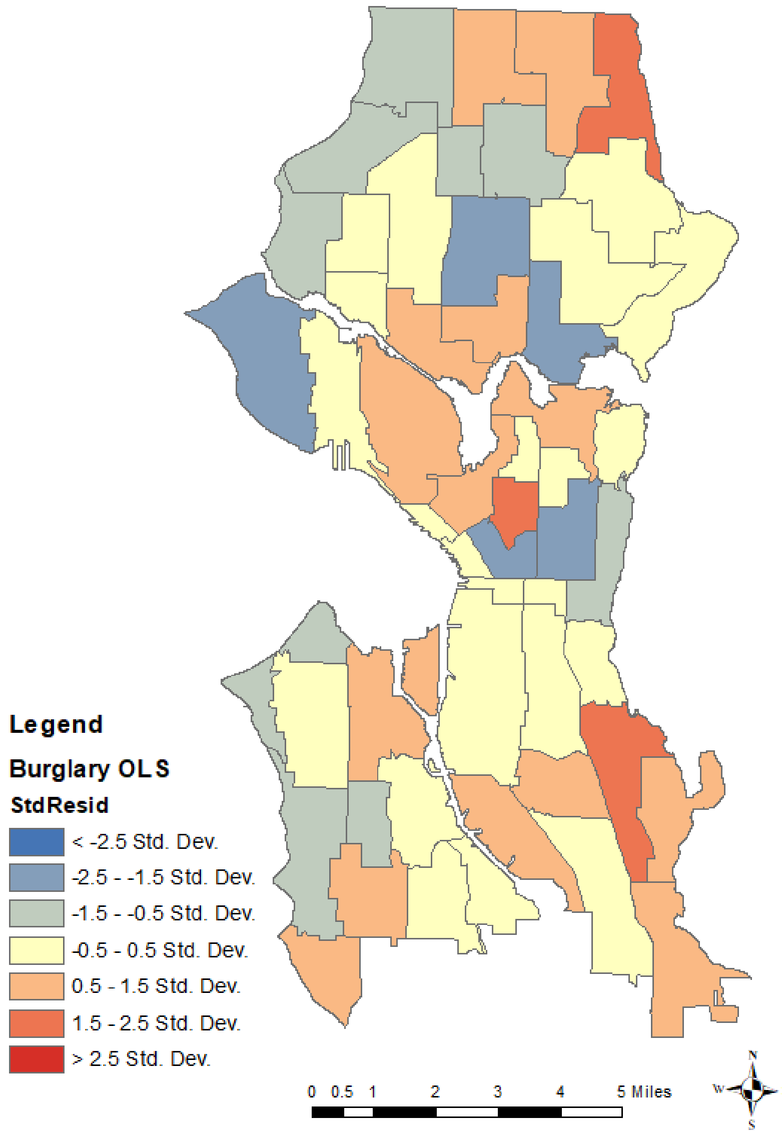

Figure 16e. Seattle map showing OLS model standardized residuals for Burglary.

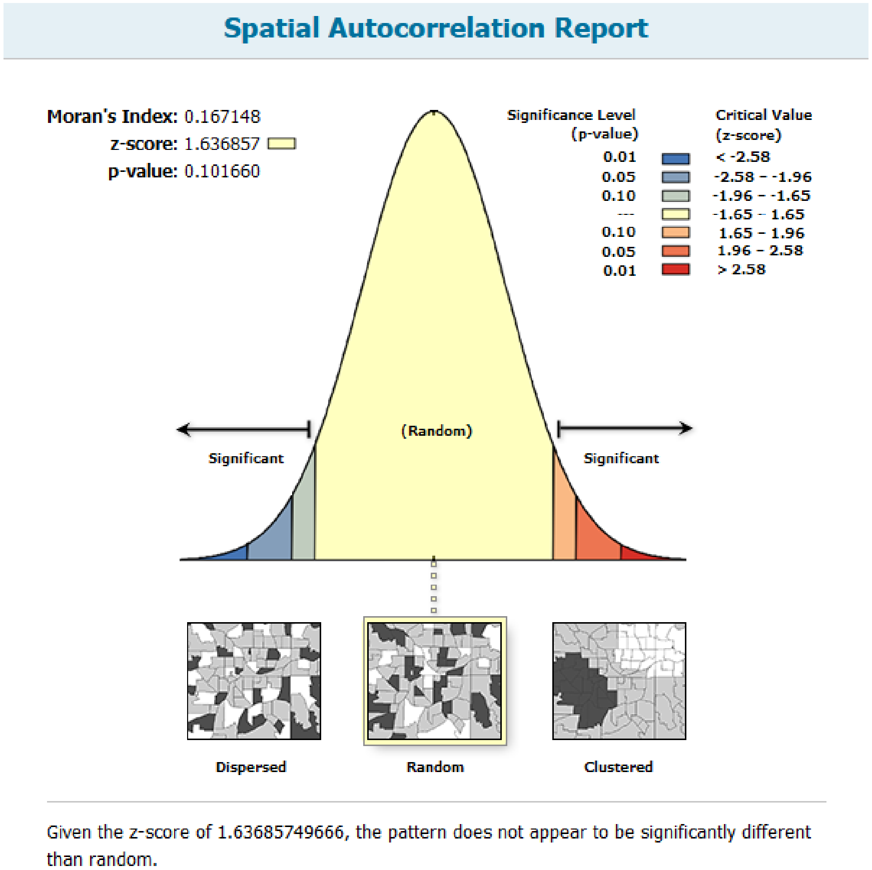

Figure 16f. Seattle spatial autocorrelation report for Burglary showing the pattern to be random.

The factors highly correlated with Auto Theft with a negative relationship were: Median household income, ATMs and Shelters. Positively correlated factors were: Bars, Transit stops, Rehabilitation facilities and Total population (Table 4g). These factors explained 80.1 percent of the phenomenon, leaving 19.9 percent unexplained. The AICc value was 507.03 (Table 4h). All variables were statistically significant, as indicated by the asterisk in the Probability [b] column.

Table 4g. Seattle OLS independent variables highly correlated with Auto Theft.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	49.929486	16.735418	2.983462	0.004593*	12.527034	3.985739	0.000244*	--------
MED_HH_INC	-0.001339	0.000319	-4.196919	0.000126*	0.000307	-4.367166	0.000073*	1.514242
BARS	4.926728	1.453319	3.389984	0.001465*	1.232481	3.997407	0.000236*	2.097574
ATMS	-2.365944	0.796134	-2.971791	0.004741*	0.766651	-3.086075	0.003466*	2.804881
TRANSIT	0.178284	0.045149	3.948798	0.000274*	0.046520	3.832412	0.000392*	2.132065
SHELTERS	-15.469891	4.424195	-3.496656	0.001073*	4.006231	-3.861458	0.000359*	1.899169
REHAB	24.511004	7.106795	3.448953	0.001234*	7.680044	3.191519	0.002582*	1.861964
POP	0.005066	0.000714	7.094184	0.000000*	0.000633	7.999095	0.000000*	1.601802

Table 4h. Seattle OLS diagnostics for Auto Theft showing model performance.

OLS Diagnostics

Input Features:	nbcra_crimes_attributes	Dependent Variable:	GTA
Number of Observations:	53	Akaike's Information Criterion (AICc) [d]:	507.032387
Multiple R-Squared [d]:	0.827849	Adjusted R-Squared [d]:	0.801070
Joint F-Statistic [e]:	30.914027	Prob(>F), (7,45) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	450.116731	Prob(>chi-squared), (7) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	4.654256	Prob(>chi-squared), (7) degrees of freedom:	0.702071
Jarque-Bera Statistic [g]:	0.001701	Prob(>chi-squared), (2) degrees of freedom:	0.999150

Checking the mapped standardized residuals (Figure 16g) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of 1.24977 (Figure 16h).

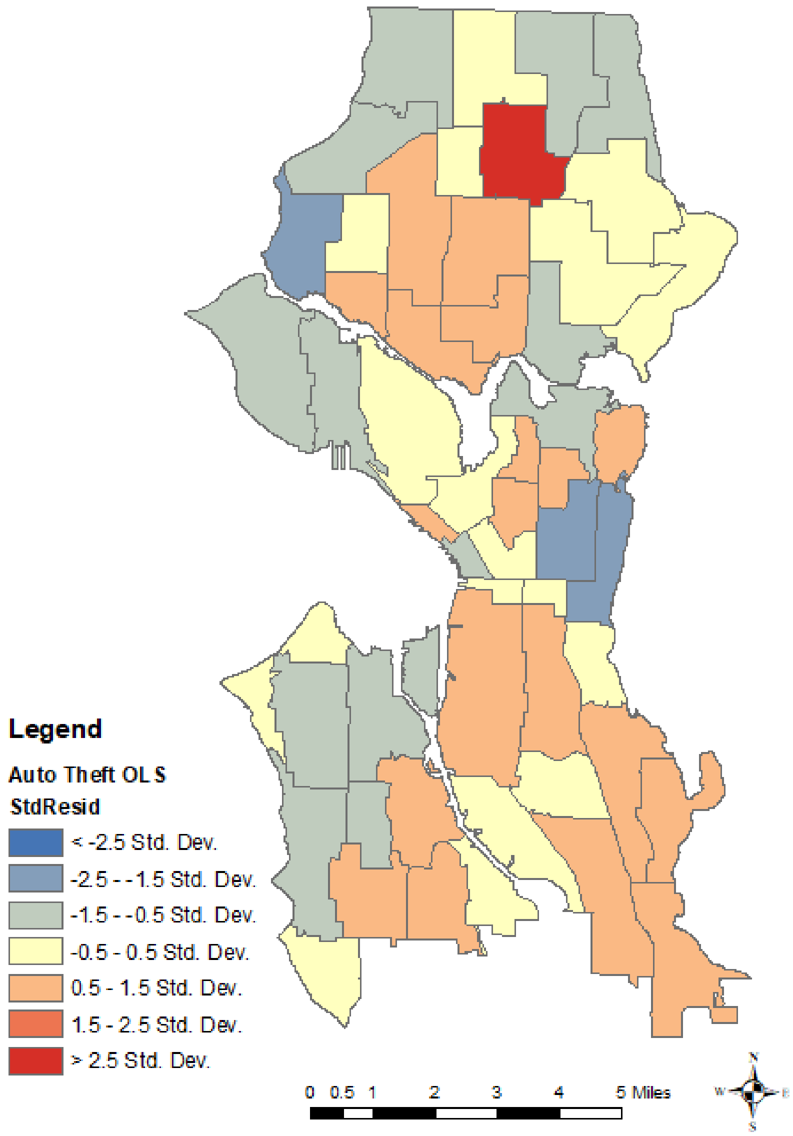

Figure 16g. Seattle map showing OLS model standardized residuals for Auto Theft.

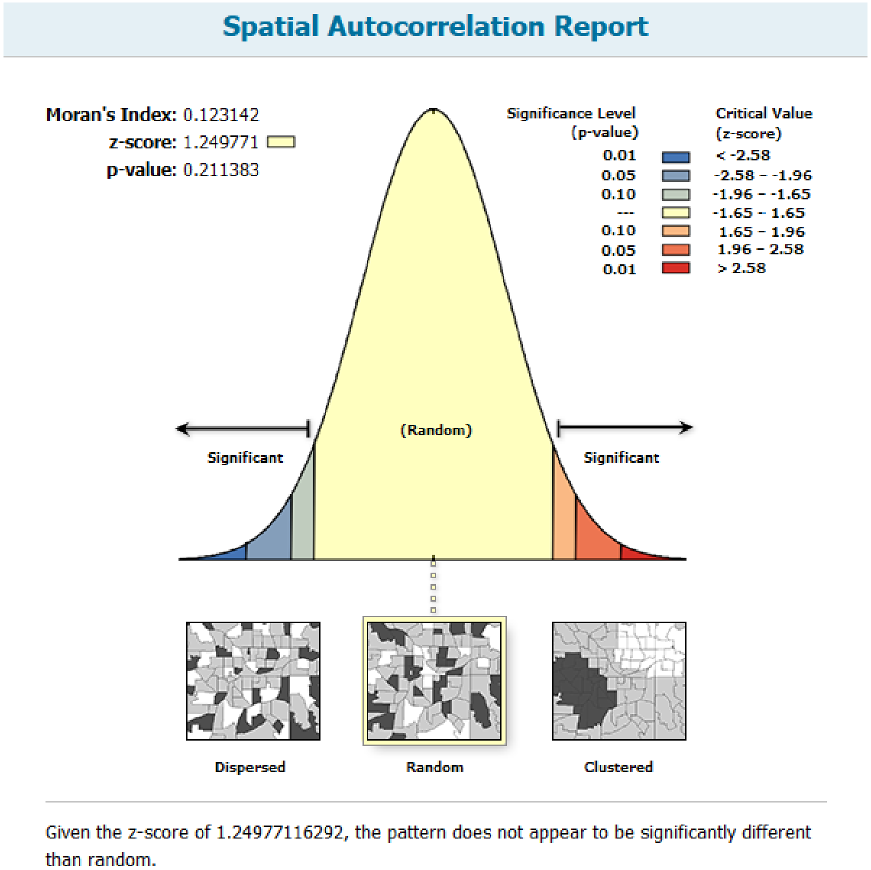

Figure 16h. Seattle spatial autocorrelation report for Auto Theft showing the pattern to be random.

There were no consistent factors across all four crime types (Table 4i). Transit stops and Total population were similar factors for three, but not the same three.

Table 4i: Seattle OLS model variables (bold = similarities, *italics* = positive relationship)

Assault	Burglary	Auto Theft	Robbery
total population	*total poulation*	*total population*	median household income
transit stops	median household income	*bars*	*hospitals*
check cashing facilities	shelters	atms	*transit stops*
clubs	*places of worship*	*transit stops*	*check cashing facilities*
police stations		shelters	*places of worship*
		rehabilitation facilities	*clubs*
			malls

5.2.3 Chicago

Geographic factors highly correlated with Aggravated Assault with a negative relationship were: Median household income, Occupied housing, and Rehabilitation facilities. The positively correlated factors were Total population, Vacant housing, Shelters, and places of Worship (Table 5a). These explained 89.0 percent of the observed phenomenon, leaving 11.0 percent unexplained. The AICc value was 879.50 (Table 5b). All variables were statistically significant, as indicated by the asterisk in the Probability [b] column.

Table 5a. Chicago OLS independent variables highly correlated with Aggravated Assault.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	87.541225	28.962127	3.022610	0.003517*	21.092978	4.150254	0.000096*	--------
TOT_POP	0.001085	0.000431	2.518089	0.014120*	0.000517	2.098901	0.039485*	2.340899
MED_HH_INC	-0.001659	0.000540	-3.072859	0.003037*	0.000437	-3.799693	0.000312*	2.418750
OCCUPIED	-0.007523	0.001784	-4.216036	0.000076*	0.001746	-4.309303	0.000055*	6.124139
VACANT	0.060935	0.010386	5.866963	0.000000*	0.008543	7.133028	0.000000*	5.577968
SHELTERS	18.777859	7.397254	2.538491	0.013390*	8.181478	2.295167	0.024766*	2.579301
WORSHIP	5.242272	0.588822	8.902979	0.000000*	0.592416	8.848964	0.000000*	2.595117
REHAB	-19.635419	8.109844	-2.421183	0.018101*	9.427663	-2.082745	0.040982*	3.035751

Table 5b. Chicago OLS diagnostics for Aggravated Assault showing model performance.

OLS Diagnostics

Input Features:	nb_attributes_regressio	Dependent Variable:	ASSAULT
Number of Observations:	77	Akaike's Information Criterion (AICc) [d]:	879.502586
Multiple R-Squared [d]:	0.900764	Adjusted R-Squared [d]:	0.890697
Joint F-Statistic [e]:	89.473108	Prob(>F), (7,69) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	664.116658	Prob(>chi-squared), (7) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	9.413086	Prob(>chi-squared), (7) degrees of freedom:	0.224342
Jarque-Bera Statistic [g]:	3.525110	Prob(>chi-squared), (2) degrees of freedom:	0.171606

Checking the mapped standardized residuals (Figure 17a) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of 0.06909 (Figure 17b).

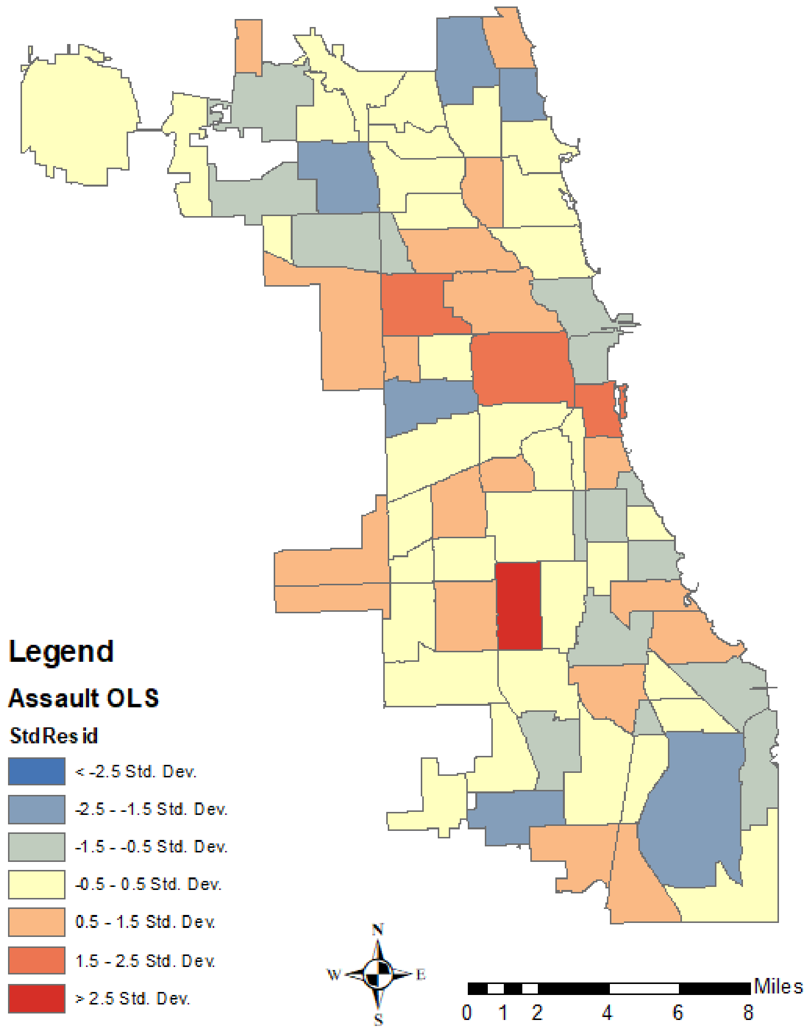

Figure 17a. Chicago map showing OLS model standardized residuals for Aggravated Assault.

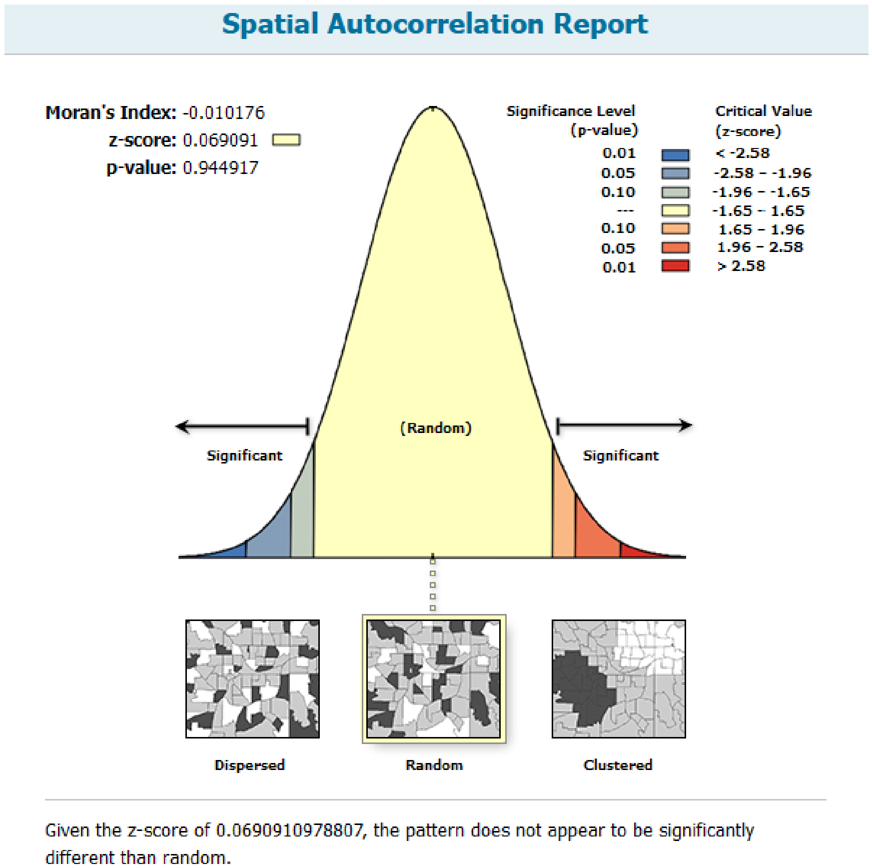

Figure 17b. Chicago spatial autocorrelation report for Aggravated Assault showing the pattern to be random.

Factors highly correlated with Robbery with a negative relationship were: Median household income, Rehabilitation facilities and Renter occupied housing. The positively correlated factors were Vacant housing, Shelters, Check cashing facilities, and Police stations (Table 5c). These explained 75.9 percent of the observed phenomenon, leaving 24.1 percent unexplained. The AICc value was 932.99 (Table 5d). Since the Koenker (BP) Statistic was significant, as indicated by the asterisk, I relied on the Robust_Pr[b] (robust probability) column to determine the significance of the coefficients. All variables were statistically significant, as indicated by the asterisk.

Table 5c. Chicago OLS independent variables highly correlated with Robbery.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	122.359979	35.851777	3.412940	0.001083*	34.261505	3.571354	0.000656*	--------
MED_HH_INC	-0.002191	0.000630	-3.480633	0.000876*	0.000510	-4.297941	0.000057*	1.641686
VACANT	0.098852	0.010427	9.480790	0.000000*	0.015577	6.346213	0.000000*	2.806264
SHELTERS	32.454653	9.980777	3.251716	0.001780*	9.485916	3.421351	0.001055*	2.344085
CKCASH	22.296509	6.124386	3.640611	0.000525*	8.253232	2.701549	0.008676*	3.035665
POLSTA	53.645707	24.206650	2.216156	0.029978*	21.532988	2.491327	0.015132*	1.232744
REHAB	-75.531499	13.176996	-5.732073	0.000000*	19.542694	-3.864948	0.000252*	4.000899
RENTER	-0.009151	0.003265	-2.803189	0.006564*	0.002880	-3.177633	0.002225*	2.823404

Table 5d. Chicago OLS diagnostics for Robbery showing model performance.

OLS Diagnostics

Input Features:	nb_attributes_regressio	Dependent Variable:	ROBBERY
Number of Observations:	77	Akaike's Information Criterion (AICc) [d]:	932.996613
Multiple R-Squared [d]:	0.782085	Adjusted R-Squared [d]:	0.759978
Joint F-Statistic [e]:	35.376723	Prob(>F), (7,69) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	202.691984	Prob(>chi-squared), (7) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	34.694406	Prob(>chi-squared), (7) degrees of freedom:	0.000013*
Jarque-Bera Statistic [g]:	1.018705	Prob(>chi-squared), (2) degrees of freedom:	0.600885

Checking the mapped standardized residuals (Figure 17c) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of 0.95656 (Figure 17d).

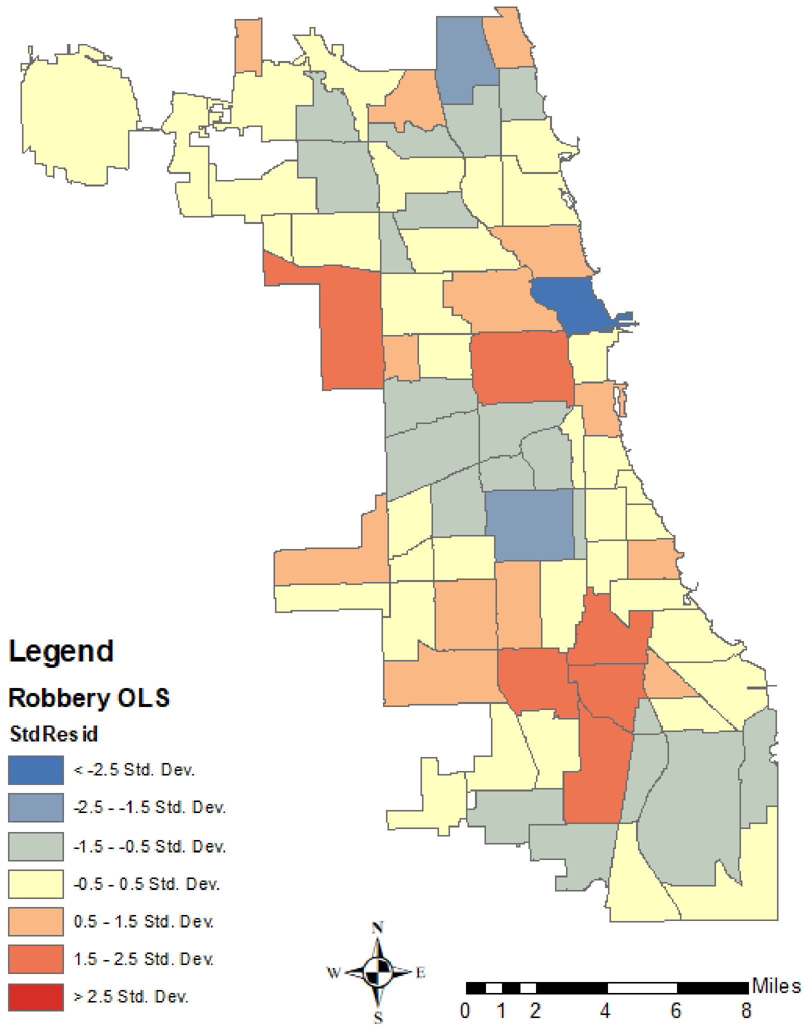

Figure 17c. Chicago map showing OLS model standardized residuals for Robbery.

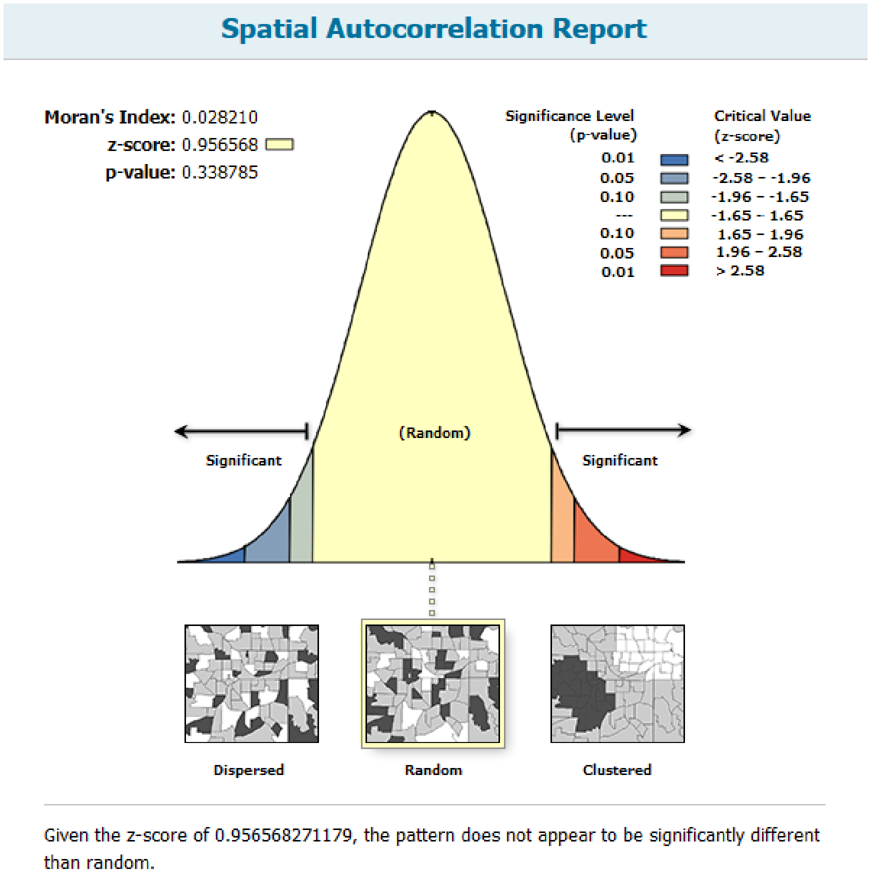

Figure 17d. Chicago spatial autocorrelation report for Robbery showing the pattern to be random.

Highly correlated factors for Burglary with a negative relationship were: Clubs and Rehabilitation facilities. Positively correlated factors were: Vacant housing and Transit stops (Table 5e). These explained 71.2 percent of the observed phenomenon, leaving 28.8 percent unexplained. The AICc value was 1007.92 (Table 5f). While all the variables were statistically significant, as indicated by the asterisk in the Probability [b] column, the Koenker BP and Jarque-Bera statistics were significant. That meant the residuals were not normally distributed and the model predictions were biased even though the Robust_Pr [b] column indicated all variables were significant.

Table 5e. Chicago OLS independent variables highly correlated with Burglary.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-64.600964	37.813549	-1.708408	0.091873	24.040360	-2.687188	0.008941*	--------
VACANT	0.121458	0.018837	6.447923	0.000000*	0.030958	3.923338	0.000201*	3.277212
TRANSIT	1.984015	0.349877	5.670612	0.000000*	0.421067	4.711879	0.000013*	2.171255
CLUBS	-25.887813	5.480538	-4.723590	0.000012*	8.120882	-3.187808	0.002125*	2.765624
REHAB	-44.962071	15.212366	-2.955626	0.004217*	14.151425	-3.177212	0.002194*	1.907934

Table 5f. Chicago OLS diagnostics for Burglary showing model performance.

OLS Diagnostics

Input Features:	nb_attributes_regressio	Dependent Variable:	BURG
Number of Observations:	77	Akaike's Information Criterion (AICc) [d]:	1007.925455
Multiple R-Squared [d]:	0.727989	Adjusted R-Squared [d]:	0.712877
Joint F-Statistic [e]:	48.173836	Prob(>F), (4,72) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	186.806774	Prob(>chi-squared), (4) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	24.747898	Prob(>chi-squared), (4) degrees of freedom:	0.000057*
Jarque-Bera Statistic [g]:	8.882863	Prob(>chi-squared), (2) degrees of freedom:	0.011779*

Checking the mapped standardized residuals (Figure 17e) for spatial autocorrelation showed that the clustered pattern of the OLS model residuals had a less than one percent likelihood of random chance, as indicated by a z-score of 3.11391 (Figure 17f).

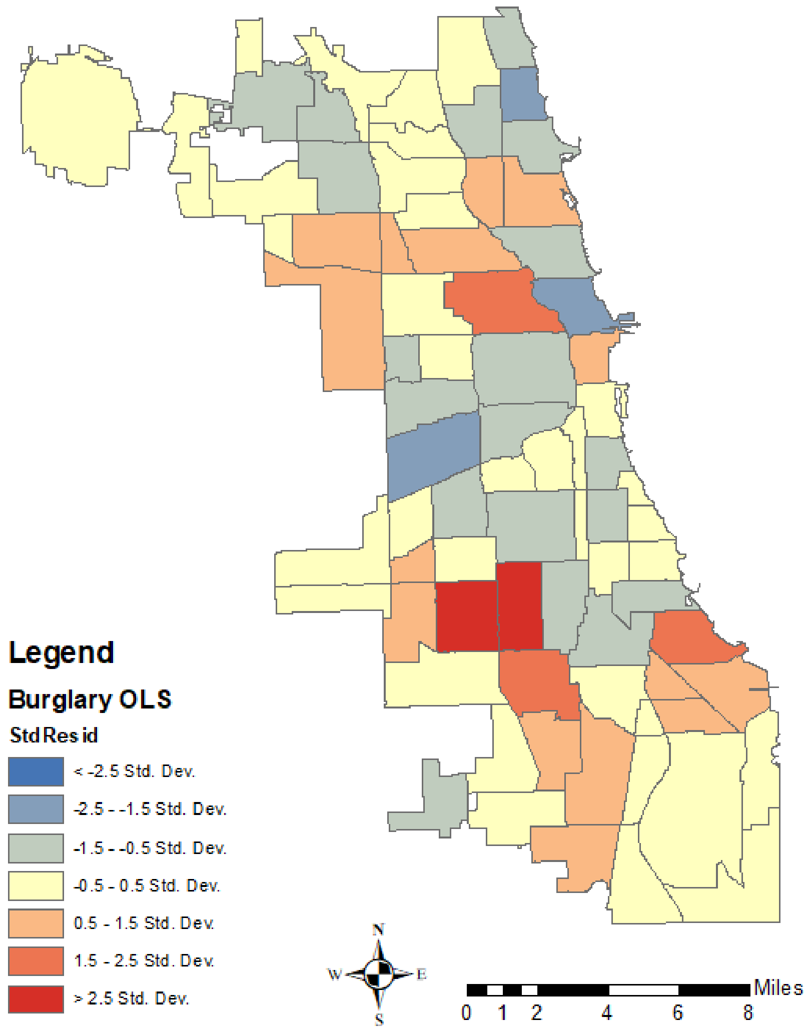

Figure 17e. Chicago map showing OLS model standardized residuals for Burglary.

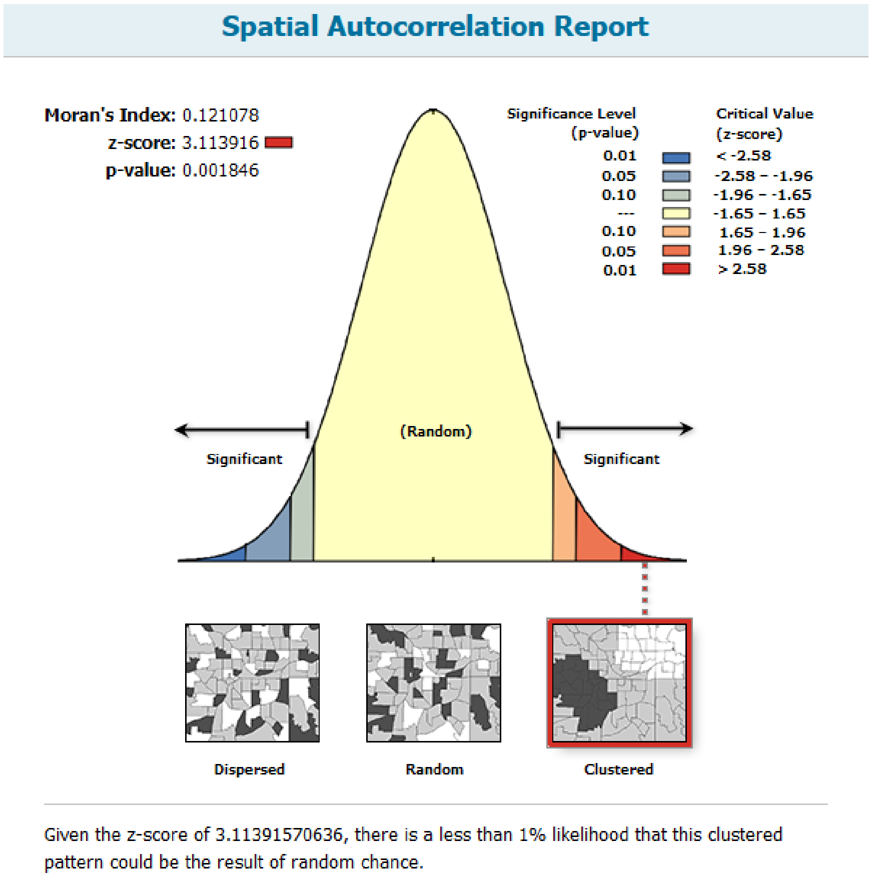

Figure 17f. Chicago spatial autocorrelation report for Burglary showing the pattern to be clustered.

The factors highly correlated with Auto Theft with a negative relationship were: Median household income, Bars, and Rehabilitation facilities. Positively correlated factors were: Total population, Vacant housing, and Shelters (Table 5g). These factors explained 72.1 percent of the phenomenon, leaving 27.9 percent unexplained. The AICc value was 939.43 (Table 5h). Since the Koenker (BP) Statistic was significant, as indicated by the asterisk, I relied on the Robust_Pr [b] (robust probability) column to determine the significance of the coefficients. All variables were statistically significant, as indicated by the asterisk.

Table 5g. Chicago OLS independent variables highly correlated with Auto Theft.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	84.710891	47.359993	1.788659	0.078000	30.925572	2.739186	0.007805*	--------
TOT_POP	0.002450	0.000570	4.300327	0.000056*	0.000985	2.487165	0.015259*	1.844449
MED_HH_INC	-0.000957	0.000785	-1.219911	0.226593	0.000476	-2.009789	0.048309*	2.301864
VACANT	0.068756	0.010814	6.357885	0.000000*	0.014150	4.859117	0.000008*	2.724416
BARS	-2.217819	1.058022	-2.096194	0.039680*	0.936571	-2.368021	0.020646*	3.848425
SHELTERS	31.231774	10.303527	3.031173	0.003415*	11.036959	2.829744	0.006074*	2.254505
REHAB	-29.736598	11.553332	-2.573855	0.012173*	12.192205	-2.438984	0.017264*	2.775709

Table 5h. Chicago OLS diagnostics for Auto Theft showing model performance.

OLS Diagnostics

Input Features:	nb_attributes_regressio	Dependent Variable:	GTA
Number of Observations:	77	Akaike's Information Criterion (AICc) [d]:	939.437006
Multiple R-Squared [d]:	0.743415	Adjusted R-Squared [d]:	0.721422
Joint F-Statistic [e]:	33.802285	Prob(>F), (6,70) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	176.671733	Prob(>chi-squared), (6) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	33.861366	Prob(>chi-squared), (6) degrees of freedom:	0.000007*
Jarque-Bera Statistic [g]:	2.522743	Prob(>chi-squared), (2) degrees of freedom:	0.283265

Checking the mapped standardized residuals (Figure 17g) for spatial autocorrelation showed the OLS model was not significantly different than a random pattern, as indicated by a z-score of 0.89472 (Figure 17h).

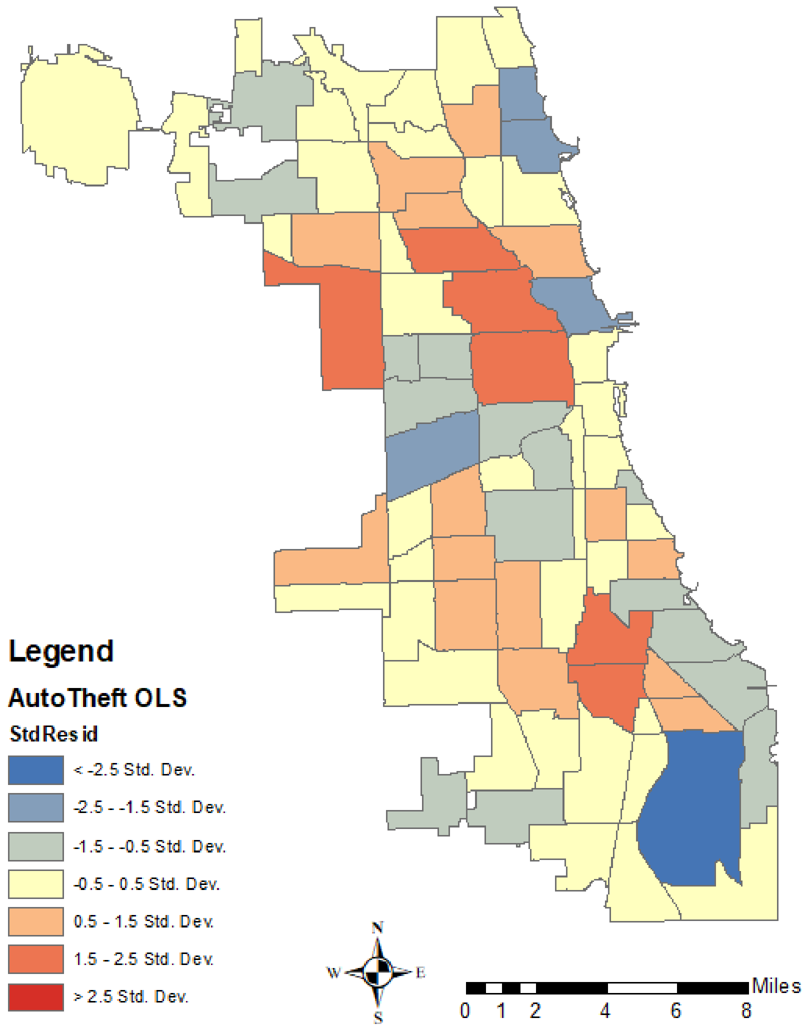

Figure 17g. Chicago map showing OLS model standardized residuals for Auto Theft.

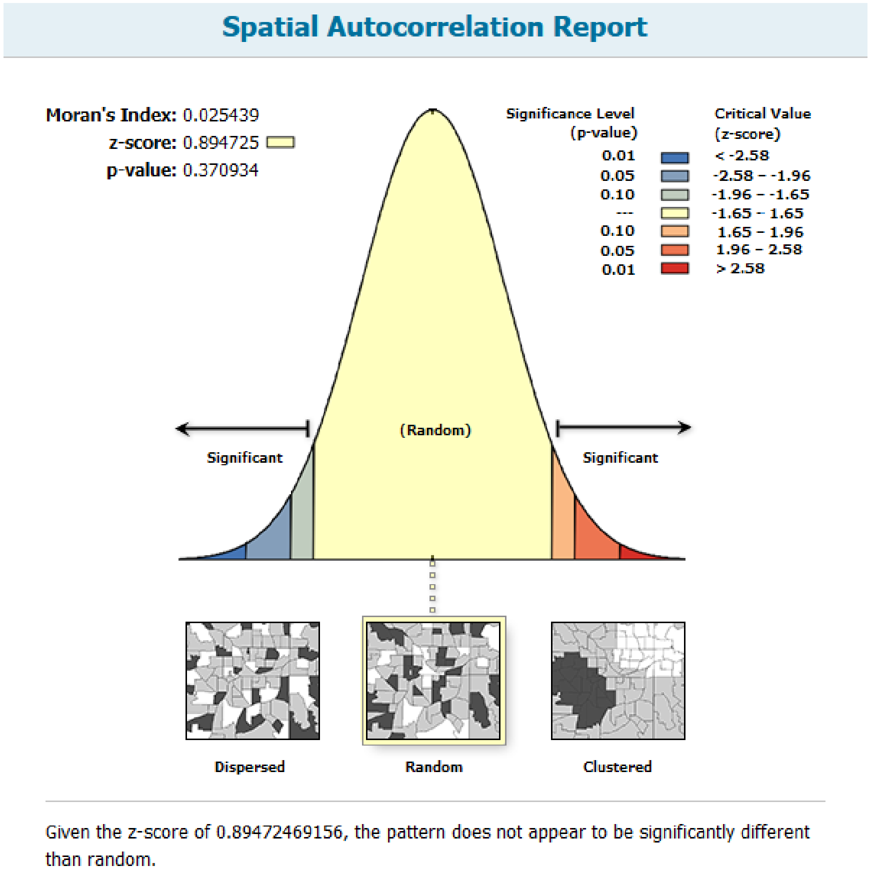

Figure 17h. Chicago spatial autocorrelation report for Auto Theft showing the pattern to be random.

The consistent factors (Table 5i) across the four crime types were Vacant housing, and Rehabilitation facilities. Shelters and Median household income were similar factors in Aggravated Assault, Auto Theft and Robbery.

Table 5i: Chicago OLS model variables (bold = similarities, *italics* = positive relationship)

Assault	Burglary	Auto Theft	Robbery
total population	***vacant housing***	*total population*	median household income
median household income	*transit stops*	median household income	***vacant housing***
occupied housing	clubs	***vacant housing***	*renter occupied housing*
vacant housing	**rehabilitation facilities**	bars	*shelters*
shelters		*shelters*	*check cashing facilities*
places of worship		**rehabilitation facilities**	*police stations*
rehabilitation facilities			**rehabilitation facilities**

5.3 Geographically Weighted Regression

Geographically Weighted Regression was applied to the OLS models to see if the model performance improved. In nearly all instances, the model did improve, if only slightly. While this approach is not novel, this step in the regression process was helpful in determining whether the global OLS model was also a good local spatial model.

5.3.1 Atlanta

The OLS model for Aggravated Assault explained 75.1 percent of the observed phenomenon. Using GWR, the model improved with a slightly higher Adjusted R-squared value of 77.8 percent. The AICc was lower at 896.23. This left 12.8 percent unexplained. (Table 6)

Applying GWR to the Robbery model improved the Adjusted R-squared value by 3.8 percent to 89.4 percent. The AICc was lowered to 796.23. This now left 7.2 percent of the observed phenomenon unexplained.

The factors correlated with Burglary in the OLS model explained 73.8 percent of the phenomenon. With GWR, the model improved yielding an Adjusted R-squared value of 80.7 percent and a slightly lower AICc value of 998.87. This left 19.3 percent unexplained.

The OLS model for Auto Theft explained 77.2 percent of the phenomenon. With GWR, the model improved with an Adjusted R-squared value of 88.3 percent and a lower AICc of 881.30. This left 11.7 percent unexplained.

Table 6. Atlanta OLS and GWR model results

		OLS	GWR
Assault			
	Adjusted R^2	0.751	0.778
	AICc	903.74	896.23
Burglary			
	Adjusted R^2	0.738	0.807
	AICc	1002.92	998.87
Auto Theft			
	Adjusted R^2	0.772	0.883
	AICc	921.67	881.30
Robbery			
	Adjusted R^2	0.858	0.894
	AICc	805.81	796.23

5.3.2 Seattle

The factors correlated with Aggravated Assault in the OLS model explained 85.6 percent of the phenomenon. With GWR, the Adjusted R-squared value increased slightly to 86.4 percent. The AICc, however, increased to 427.26. That left 13.6 percent unexplained. (Table 7)

The OLS model for Robbery explained 85.1 percent of the phenomenon. Testing the model with GWR yielded a slightly higher Adjusted R-squared percentage of 85.6. This left 14.4 percent unexplained. The AICc increased slightly to 442.45.

The factors correlated with Burglary in the OLS model explained 85.5 percent of the observed phenomenon. The GWR test with the same model had a slightly higher Adjusted R-squared of 86.3 percent and a higher AICc of 529.19, leaving 13.7 percent unexplained.

Factors correlated with Auto Theft in the OLS model explained 80.1 percent of the phenomenon. The model improved with an Adjusted R-squared value of 93.1 percent. Here also, the AICc increased to 542.01. This left 6.9 percent unexplained.

Table 7. Seattle OLS and GWR model results

		OLS	GWR
Assault			
	Adjusted R^2	0.856	0.864
	AICc	424.03	427.26
Burglary			
	Adjusted R^2	0.855	0.863
	AICc	528.16	529.19
Auto Theft			
	Adjusted R^2	0.801	0.931
	AICc	507.03	542.01
Robbery			
	Adjusted R^2	0.851	0.856
	AICc	440.20	442.45

5.3.3 Chicago

The factors correlated with Aggravated Assault in the OLS model explained 89 percent of the phenomenon. With GWR, the percentage was a little higher at 89.4 percent. That left just 11.6 percent unexplained. The AICc value increased slightly to 880.10. (Table 8)

The OLS model for Robbery explained 75.9 percent of the phenomenon. With GWR, the Adjusted R-squared percentage was slightly higher at 77.2 percent. This left 22.8 percent unexplained and the AICc value decreased slightly to 931.69.

Factors correlated with Burglary in the OLS model explained 71.2 percent of the phenomenon. With GWR, the percentage increased to 84.6 percent, leaving 15.4 percent unexplained. The AICc value decreased to 979.97. Additionally, recall that the OLS model produced clustered standard residuals. After performing GWR, the residuals were no longer clustered, resembling a random distribution (Figure 18).

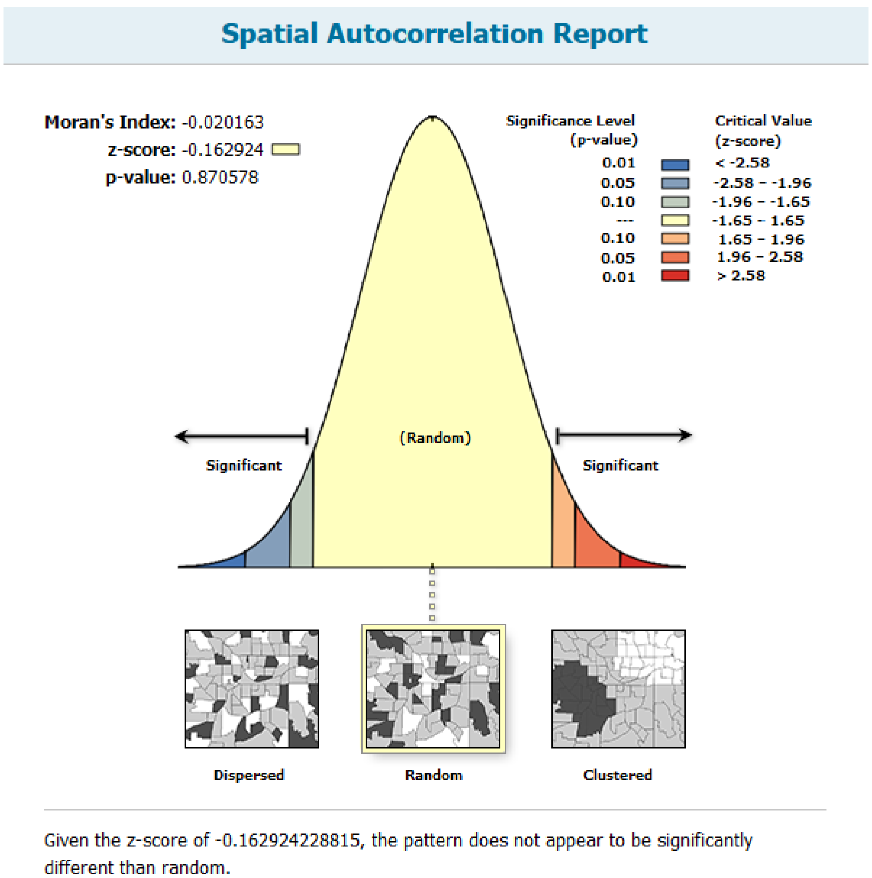

Figure 18. Chicago spatial autocorrelation report showing a random pattern after performing geographically weighted regression with the OLS model for Burglary.

The factors correlated with Auto Theft in the OLS model explained 72.1 percent of the phenomenon. With GWR, the Adjusted R-squared percentage was slightly higher at

75.9 percent, leaving 24.1 percent unexplained. The AICc value decreased slightly to 933.99.

Table 8. Chicago OLS and GWR model results

		OLS	GWR
Assault			
	Adjusted R^2	0.890	0.894
	AICc	879.50	880.10
Burglary			
	Adjusted R^2	0.712	0.846
	AICc	1007.92	979.97
Auto Theft			
	Adjusted R^2	0.721	0.759
	AICc	939.43	933.99
Robbery			
	Adjusted R^2	0.759	0.772
	AICc	932.99	931.69

5.4 Regional Factor Model

This section applied a regionally similar GWR model for each crime type in the three cities. The model, named GWR-2, contained the following factors: Median household income, Shelters, places of Worship, Renter occupied housing, Vacant housing, and Transit stops. These factors were common across all three cities, with only Median household income as the negatively correlated relationship. The GWR-2 model was compared to the

GWR model specified for the respective crime type (GWR-1) to determine if using the second model containing identical factors improved results.

5.4.1 Atlanta

The results for assault improved slightly using the GWR-2 model with an Adjusted R-squared value of 0.787 and an AICc of 895.76 (Table 9). The standard residuals were not clustered.

Table 9. Atlanta: comparison of GWR models. GWR-1 is the specified model for the crime type. GWR-2 is the similar factor model used for all crime types.

		GWR-1	GWR-2
Assault			
	Adjusted R^2	0.778	0.787
	AICc	896.23	895.76
Burglary			
	Adjusted R^2	0.807	0.703
	AICc	998.87	1041.68
Auto Theft			
	Adjusted R^2	0.883	0.830
	AICc	881.30	910.43
Robbery			
	Adjusted R^2	0.894	0.875
	AICc	796.23	815.75

The burglary model results revealed the GWR-2 model was not as effective. The Adjusted R-squared value was 10 percent less than the specified model at 0.703. The AICc was also higher at 1041.68. The residuals were randomly distributed.

Model results for robbery using the GWR-2 model also did not perform as well as the specified model. The Adjusted R-squared value was 0.875, about two percent less than the GWR-1 model. The AICc was higher with a value of 815.75. The standard residuals were in the range of a less than 5 percent likelihood of random chance clustering (Figure 19).

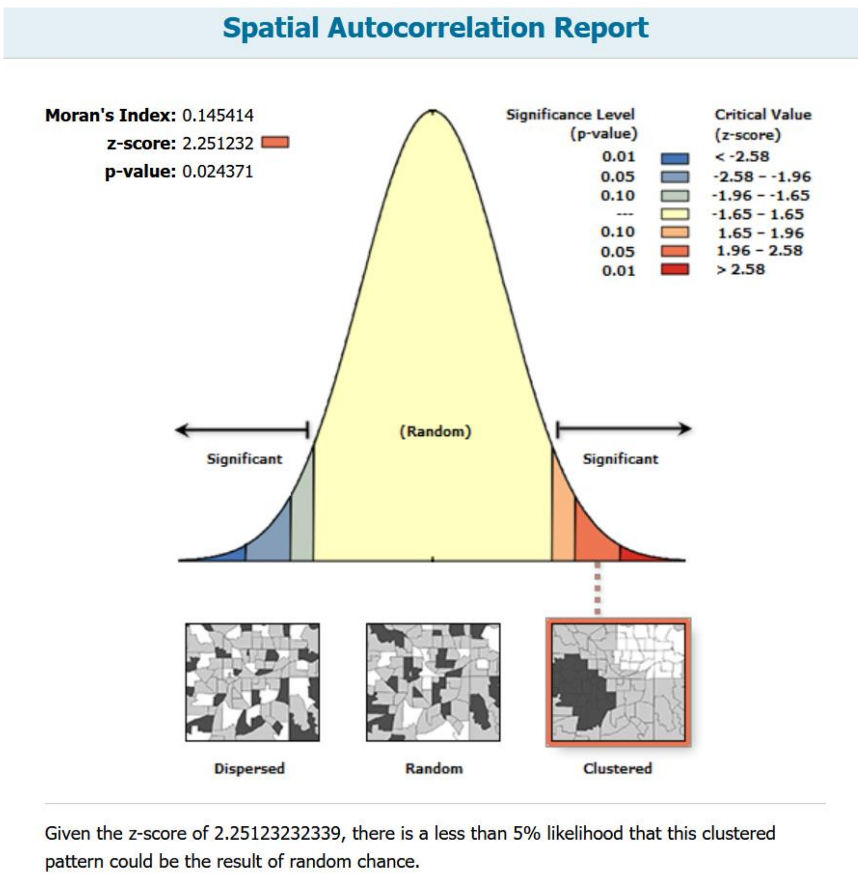

Figure 19. Atlanta spatial autocorrelation report for robbery showing clustering of standard residuals using the similar factor model.

The auto theft model results also showed slightly less performance than the GWR-1 model with an Adjusted R-squared value of 0.830. This was a 5 percent decrease. The AICc was higher at 910.43 and the residuals were randomly distributed.

Using the GWR-2 factor model improved the results for assault, but not the other crime types. In all, there was an average of 20 percent of the crime unexplained using this model in Atlanta.

5.4.2 Seattle

The model results for assault did not perform as well as the corresponding GWR-1 model. The Adjusted R-squared value was just under 11 percent lower at 0.758 and the AICc was higher at 451.65 (Table 10). The standard residuals were randomly distributed.

Table 10. Seattle: comparison of GWR models. GWR-1 is the specified model for the crime type. GWR-2 is the similar factor model used for all crime types.

		GWR-1	GWR-2
Assault			
	Adjusted R^2	0.864	0.758
	AICc	427.26	451.65
Burglary			
	Adjusted R^2	0.863	0.890
	AICc	529.19	520.13
Auto Theft			
	Adjusted R^2	0.931	0.791
	AICc	542.01	511.42
Robbery			
	Adjusted R^2	0.856	0.735
	AICc	442.45	473.47

The results of the GWR-2 model with burglary improved the Adjusted R-squared value to 0.890 and lowered the AICc to 520.13. The residuals, however, showed a less than 10 percent likelihood the clustering was random chance (Figure 20).

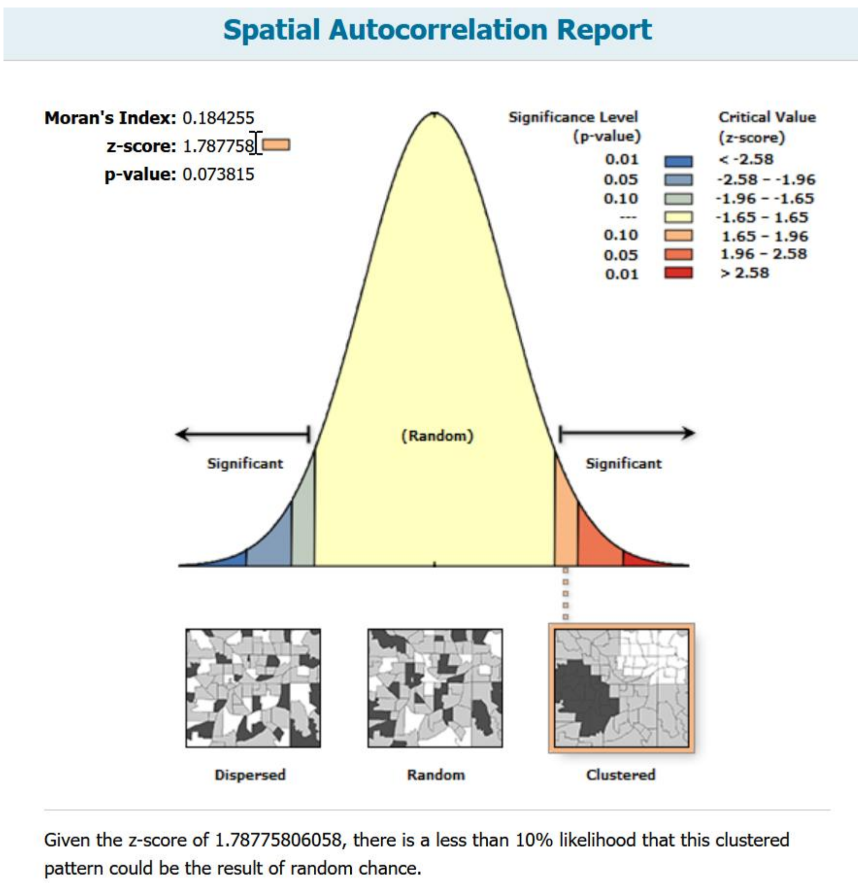

Figure 20a. Seattle spatial autocorrelation report for burglary showing clustering of standard residuals using the similar factor model.

The GWR-2 model also did not perform well for robbery. The Adjusted R-squared value was more than 10 percent less than the specified model at 0.735. The AICc was higher at 473.47. Unlike the GWR-2 model performance in Atlanta for this crime type, the standard residuals were randomly distributed.

The GWR-2 model results for auto theft did not perform as well as the GWR-1 model. Although the AICc was lower than the specified model at 511.42, the Adjusted R-squared value was 0.791. Like the specified model, the standard residuals were clustered with a less than 10 percent likelihood of random chance (Figure 20b).

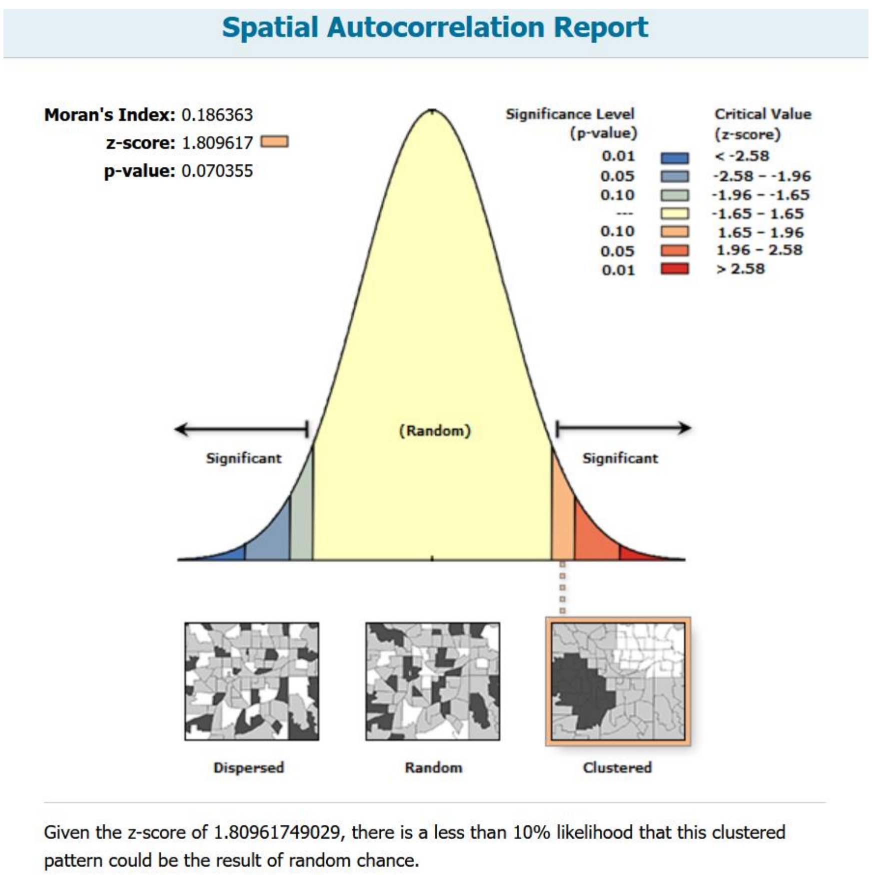

Figure 20b. Seattle spatial autocorrelation report for auto theft showing clustering of standard residuals using the similar factor model.

Using the GWR-2 factor model only improved results with the burglary crime type, though the residuals were clustered. As with Atlanta, there was an average of about 20 percent of the crime phenomenon left unexplained.

5.4.3 Chicago

The model results for assault performed slightly better using the GWR-2 model with an Adjusted R-squared value of 0.905 (Table 11). The AICc was also slightly higher at 881.43. The standard residuals were randomly distributed.

Table 11. Chicago: comparison of GWR models. GWR-1 is the specified model for the crime type. GWR-2 is the similar factor model used for all crime types.

		GWR-1	GWR-2
Assault			
	Adjusted R^2	0.894	0.905
	AICc	880.10	881.43
Burglary			
	Adjusted R^2	0.846	0.900
	AICc	979.97	964.36
Auto Theft			
	Adjusted R^2	0.759	0.843
	AICc	933.99	897.67
Robbery			
	Adjusted R^2	0.772	0.893
	AICc	931.69	892.11

The GWR-2 model showed improved performance with burglary, as well. The Adjusted R-squared value was about 6 percent higher at 0.900 and the AICc was lower at 964.36. The standard residuals were randomly distributed.

For auto theft, the GWR-2 model also performed better with an Adjusted R-squared value of 0.843. The AICc was also lower at 897.67. However, there was clustering with the standard residuals (Figure 21).

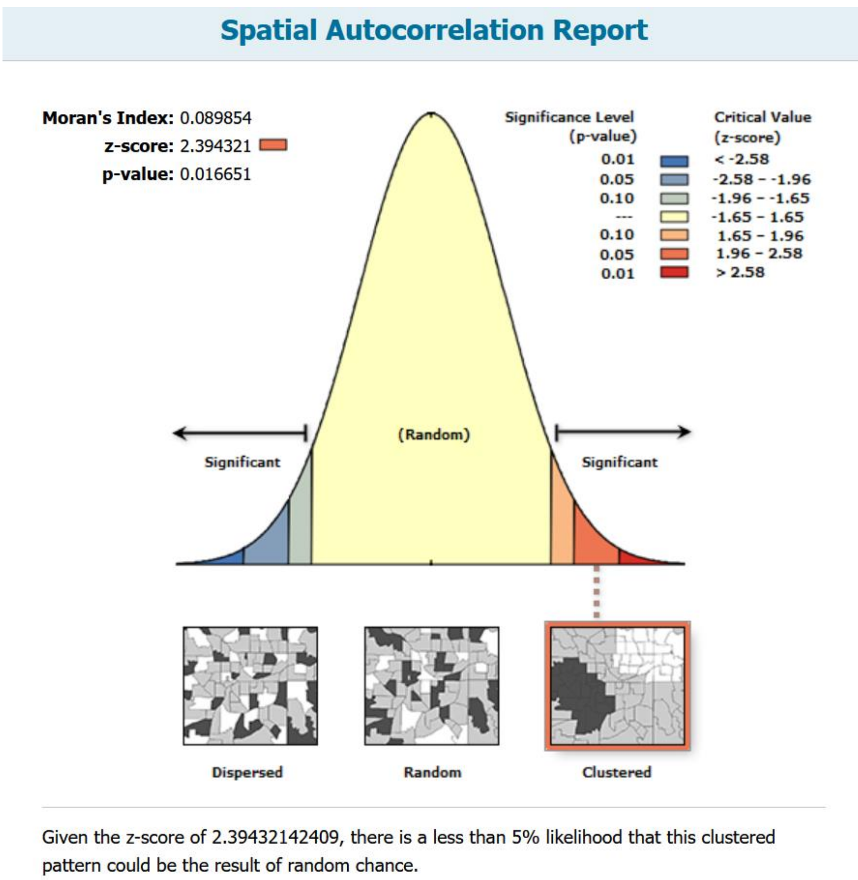

Figure 21. Chicago spatial autocorrelation report for auto theft showing clustering of standard residuals using the similar factor model.

Using the GWR-2 model, results for robbery showed improvement with a higher Adjusted R-squared of 0.893 and a lower AICc of 892.11. The standard residuals were randomly distributed.

Using the GWR-2 factor model improved results for all four crime types over the GWR-1 specified models, though there was clustering with the residuals for auto theft. An average of 12 percent of the crime phenomenon was unexplained.

5.5 Temporal

Previous studies have examined seasonal trends of crime, finding that seasonality may be relevant in the increase and/or decrease in crime (Andresen and Malleson 2013; Cohn and Rotton 2000; and Linning 2015). This section contains the results of observed temporal patterns to ascertain whether any similarities existed among the three cities. By using temporal heatmaps in both R and excel to visualize the month, day, and time of crime events, the patterns were much clearer and, in some cases, not very clear at all. Bar charts were also used to provide a different visualization of the data. The time series-calendar heatmap images are presented in Appendix C.

5.5.1 Atlanta

There was no clear pattern for day of the week or month of the year when examining the calendar heatmaps for Aggravated Assault (Appendix C). There were a few days that stood out; however, those days were not consistent across each year. There was also missing data from 2011 to 2013 as indicated by blanks in the calendar. However, when visualizing the aggregated annual data in a bar chart, Saturday was the highest reported day of the week (Figures 22a-b).

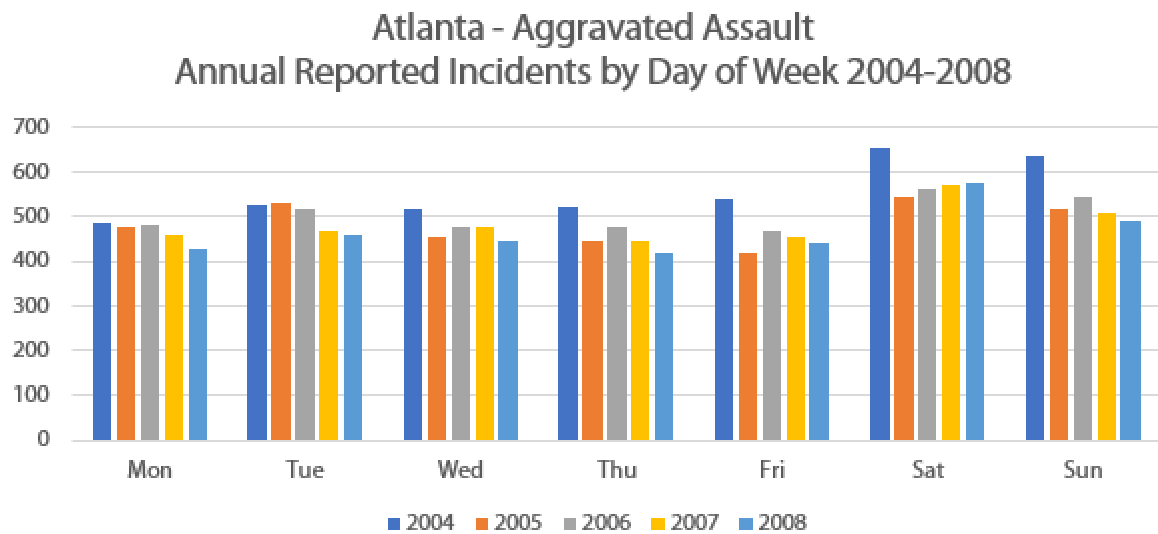

Figure 22a. Day of week: Atlanta citywide frequency per year for aggravated assault, 2004-2008.

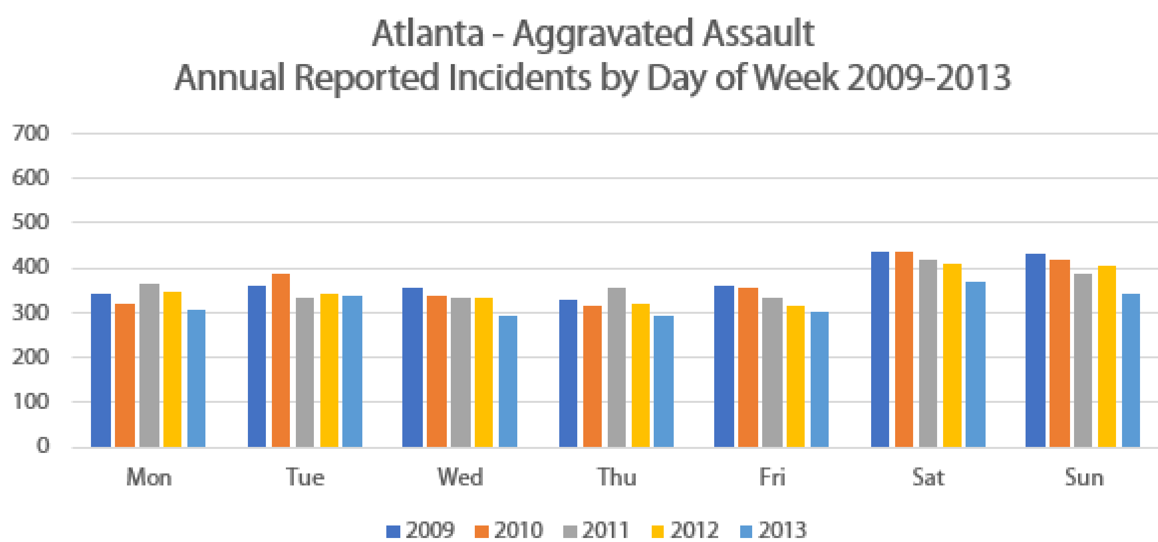

Figure 22b. Day of week: Atlanta citywide frequency per year for aggravated assault, 2009-2013.

An overall pattern of decrease in reported incidents could be seen with the monthly heat map (Figure 22c).

Atlanta - Aggravated Assault
Annual Reported Incidents by Month

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
January	309	273	273	226	262	218	180	167	157	190
February	259	245	211	216	233	206	161	175	181	138
March	359	265	290	316	228	232	219	191	218	182
April	326	285	247	255	228	234	231	213	225	196
May	396	329	334	322	287	228	235	273	175	198
June	328	280	330	245	306	251	218	219	218	220
July	339	319	314	256	328	258	255	239	217	205
August	357	344	337	304	301	206	231	226	245	203
September	326	308	308	304	269	211	232	235	202	206
October	354	273	322	275	264	217	229	186	198	182
November	285	249	238	249	227	187	193	205	150	149
December	245	225	228	221	331	164	183	196	182	173

Low High

Figure 22c. Month heatmap: Atlanta citywide counts per year for aggravated assault.

In the time-of-day chart (Figure 22d), the evening hours between 1801 and 0000 were the most frequently reported times for aggravated assault for all 10 years.

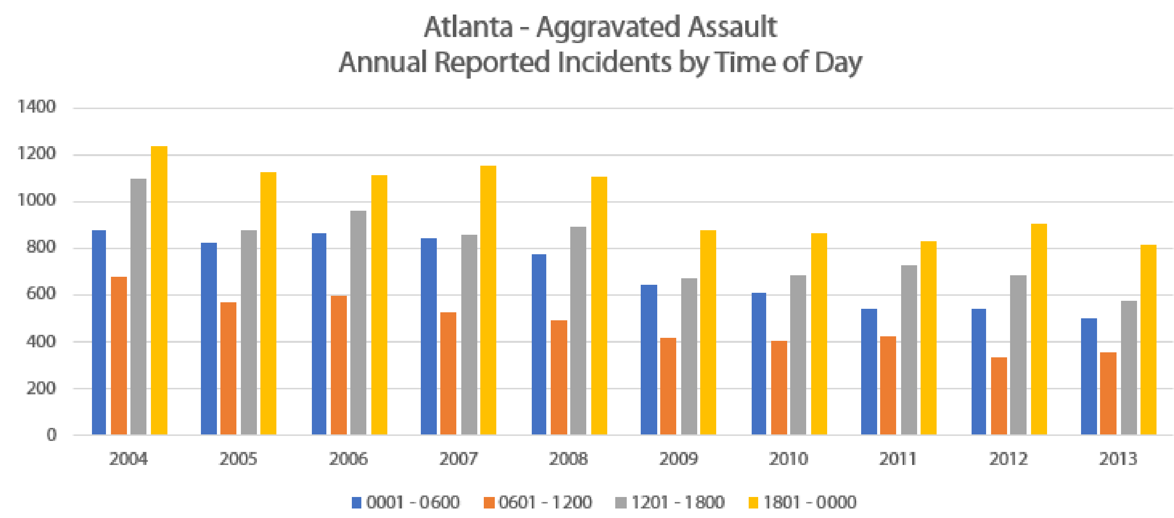

Figure 22d. Time of day: Atlanta citywide frequency per year for aggravated assault.

With Burglary, the pattern was a little easier to see in the calendar heatmaps (Appendix C). Incidents occurred more frequently during the weekdays than on the weekends. When visualizing the aggregated annual data with a bar chart, Saturday was the highest reported day of the week (Figures 22e-f).

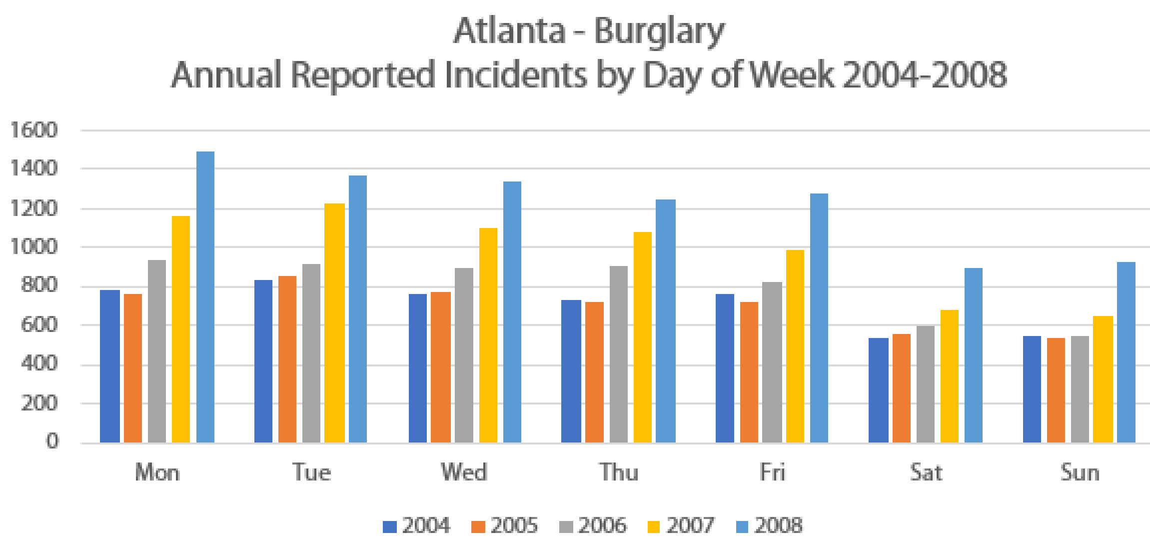

Figure 22e. Day of week: Atlanta citywide frequency per year for burglary, 2004-2008.

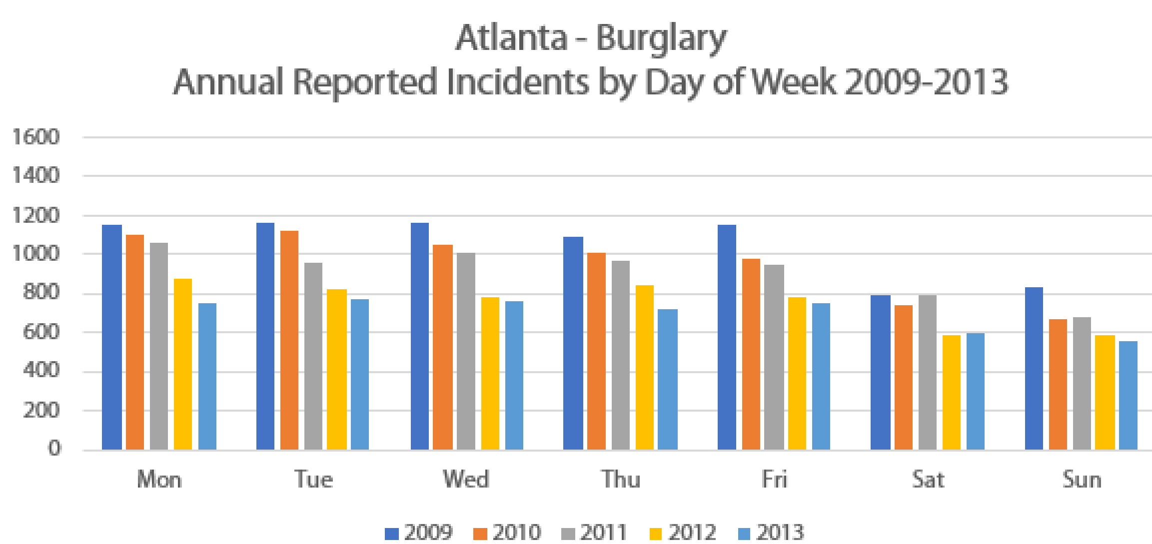

Figure 22f. Day of week: Atlanta citywide frequency per year for burglary, 2009-2013.

Moreover, the summer months (Figure 22g) were consistent with a higher frequency of incidents. The time between 0601 and 1200 was the most frequently reported times for Burglary. (Figure 22h)

Atlanta - Burglary
Annual Reported Incidents by Month

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
January	474	377	415	476	591	678	573	474	468	510
February	329	329	332	405	432	452	395	329	299	342
March	373	337	391	445	566	540	504	437	383	353
April	340	390	383	504	636	586	553	505	400	382
May	399	431	437	492	675	600	585	571	402	491
June	366	406	444	562	656	692	508	588	425	430
July	445	400	507	698	773	720	599	612	440	420
August	427	528	571	669	853	660	608	700	552	408
September	476	436	533	611	757	523	574	561	478	391
October	486	402	562	657	757	564	591	531	500	411
November	412	414	527	671	771	637	597	536	439	350
December	411	477	511	677	1073	698	583	563	477	432

Low High

Figure 22g. Month heatmap: Atlanta citywide frequency per year for burglary.

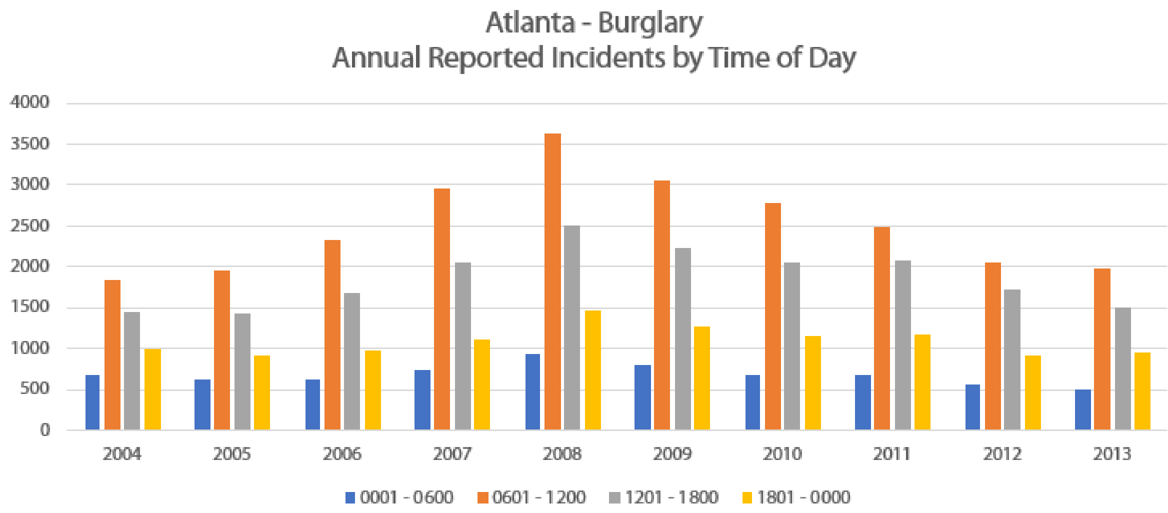

Figure 22h. Time of day: Atlanta citywide frequency per year for burglary.

There is no real discernable pattern in the calendar days for Auto Theft. Like Assaults, there were some days and months that were especially high (Appendix C), but not with any consistency. The aggregated annual data with a bar chart, showed that Saturday was the highest reported day of the week (Figures 22i-j).

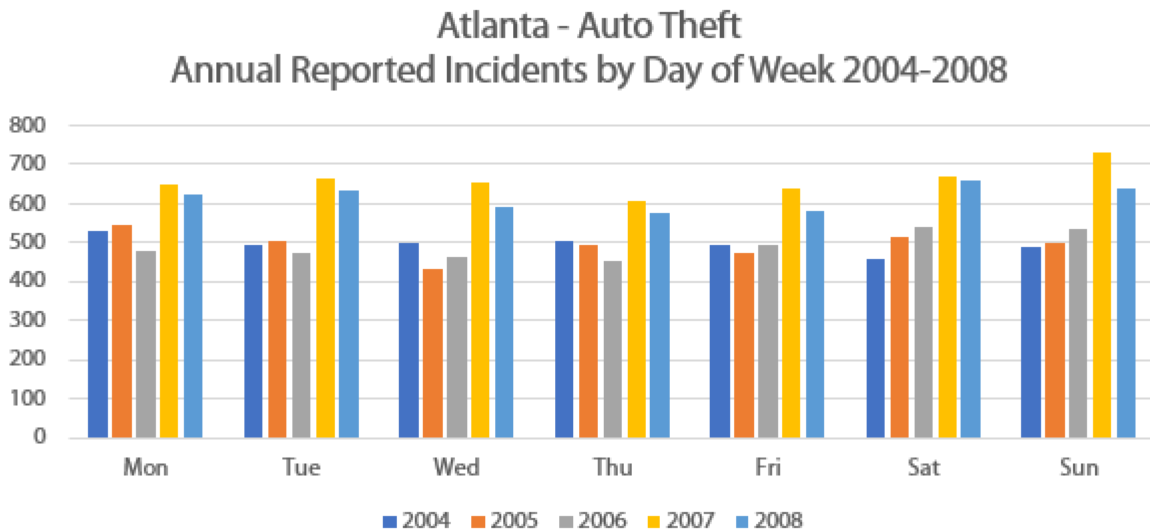

Figure 22i. Day of week: Atlanta citywide frequency per year for auto theft, 2004-2008.

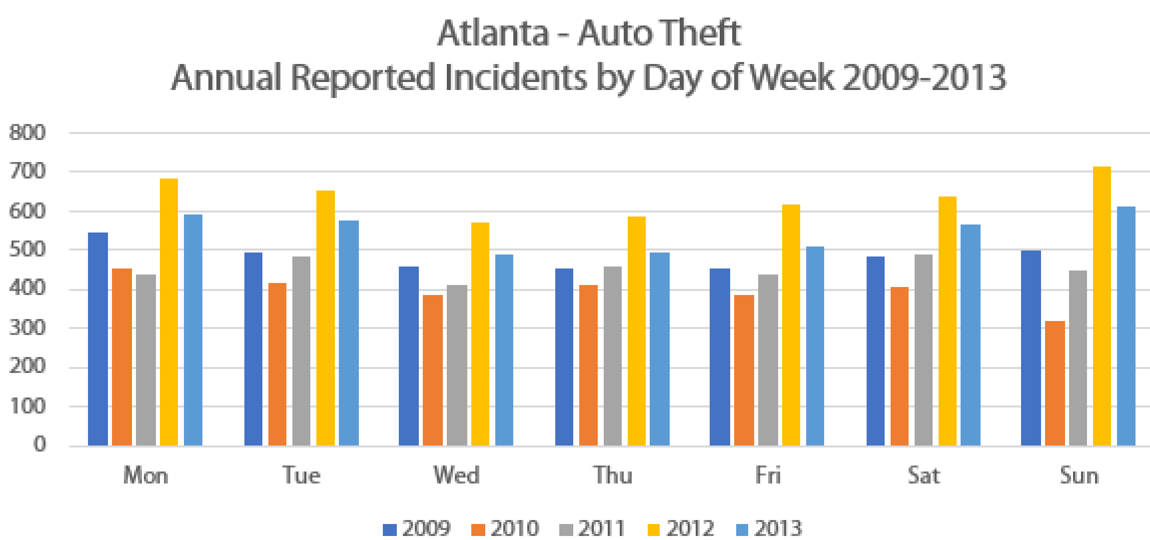

Figure 22j. Day of week: Atlanta citywide frequency per year for auto theft, 2009-2013.

There was no consistent patter with the month heatmap (Figure 22k). In contrast, with the bar chart for Time of Day (Figure 22l), it was clear that the most frequently reported time was between the hours 1801 and 0000.

Atlanta - Auto Theft
Annual Reported Incidents by Month

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
January	344	260	258	305	330	307	241	211	391	419
February	284	239	201	266	343	228	153	143	268	314
March	307	261	256	321	316	299	199	220	299	334
April	257	328	257	282	291	295	229	234	286	294
May	282	275	260	414	323	320	241	264	374	320
June	297	318	297	518	303	322	238	311	441	348
July	303	342	317	510	418	317	244	329	420	337
August	297	339	347	438	431	300	243	276	359	311
September	271	346	320	399	410	255	258	227	380	286
October	299	264	296	434	385	228	227	301	403	285
November	279	239	291	374	331	269	268	308	386	258
December	255	249	338	352	519	247	234	344	454	335

Low High

Figure 22k. Month heatmap: Atlanta citywide frequency per year for auto theft.

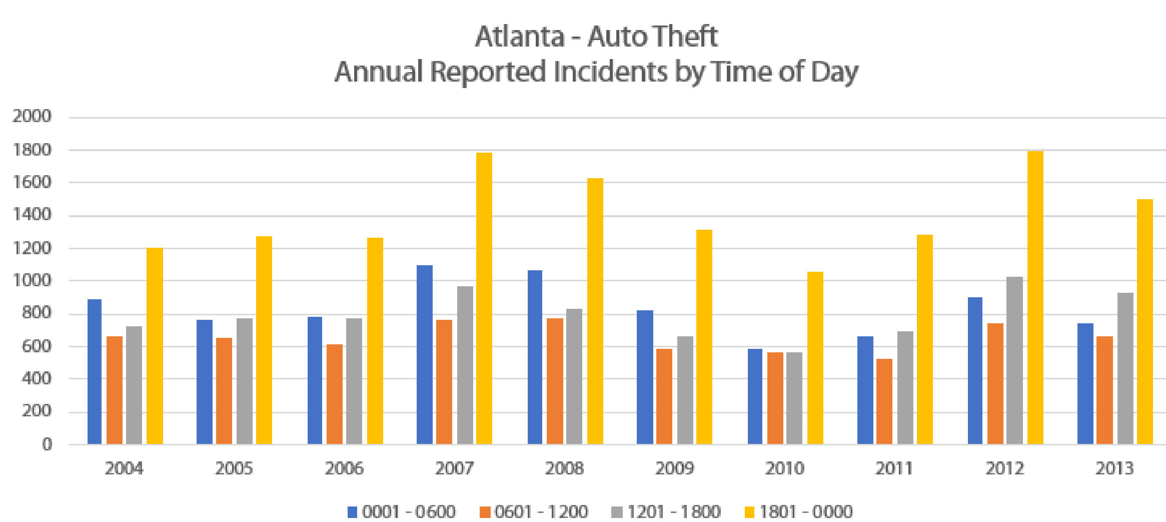

Figure 22l. Time of day: Atlanta citywide frequency per year for auto theft.

Robbery was much like Auto Theft and Assault. There was no real pattern with regard to the day of the week or month of the year (Appendix C). Data was missing in this crime type as well. And there appeared to be days with high reported rates, though not consistent across each year.

When visualizing the aggregated annual data with a bar chart, it was slightly easier to see the irregular pattern for the day of the week (Figures 22m-n).

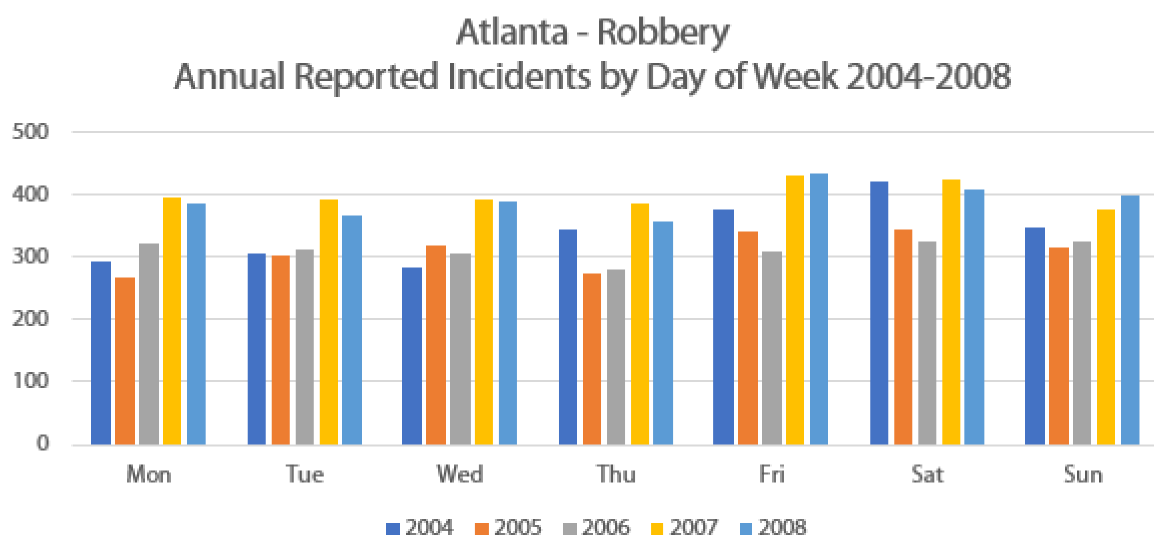

Figure 22m. Day of week: Atlanta citywide frequency per year for robbery, 2004-2008.

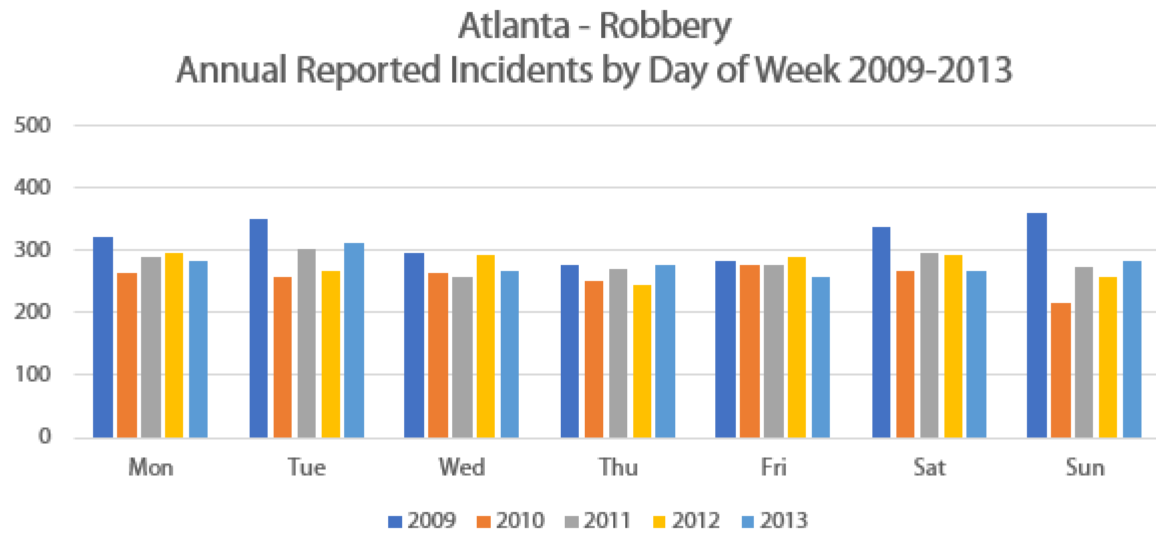

Figure 22n. Day of week: Atlanta citywide frequency per year for robbery, 2009-2013.

The monthly heat map showed there was a decrease in reported robbery after 2008, aside from that, there did not appear to be a consistent pattern by month (Figure 22o).

Atlanta - Robbery
Annual Reported Incidents by Month

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
January	211	190	190	223	247	225	150	136	138	173
February	158	113	126	137	139	121	95	110	91	146
March	213	151	157	209	220	160	128	136	134	130
April	193	211	182	216	205	135	158	161	151	138
May	225	171	155	232	213	169	146	196	183	204
June	216	156	164	252	195	194	173	166	176	153
July	245	212	207	259	210	220	159	175	197	176
August	193	214	177	266	285	215	178	203	177	160
September	159	197	179	255	241	183	168	149	173	182
October	213	172	217	275	278	206	168	178	163	147
November	185	194	225	269	189	199	143	198	180	177
December	155	179	200	205	318	196	133	160	175	159

Low High

Figure 22o. Month heatmap: Atlanta citywide frequency per year for robbery.

As with Auto Theft and Assaults, the most frequently reported time for Robbery was 1801 to 0000 (Figure 22p).

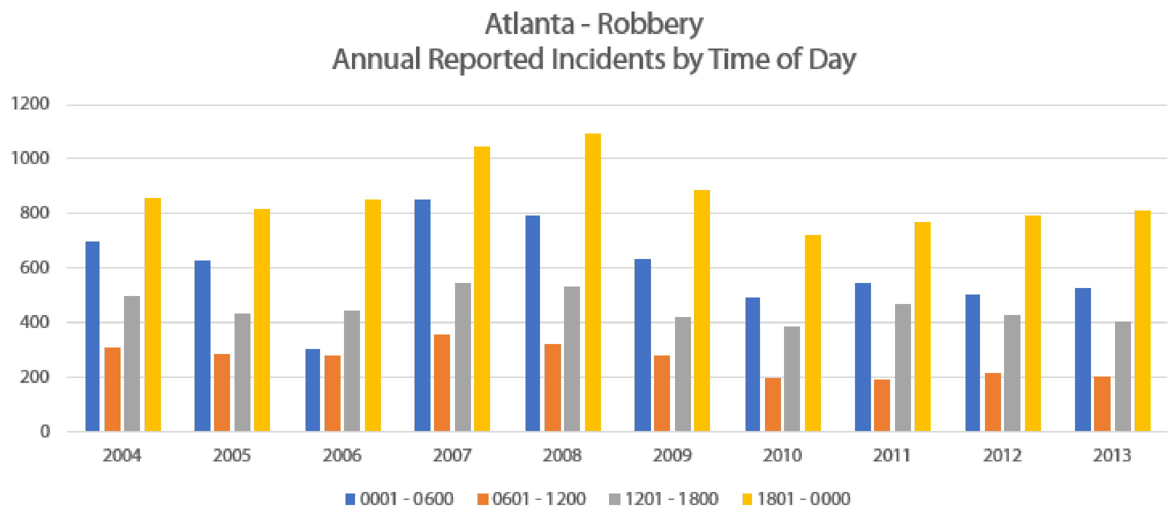

Figure 22p. Time of day: Atlanta citywide frequency per year for robbery.

In review, it was clear that there was an overall decrease in Assaults and that the warmer months were high in June, July, August, and September. While Burglary had an overall monthly decrease each year after 2008, there wasn't a dramatic change until 2011. Auto Theft, as the box plots showed (Figures 10a-10d), decreased, and then increased before seeing lower numbers again. Robbery had an overall decrease after 2008.

5.5.2 Seattle

There was no visible day of week pattern with Assault in viewing the calendar heat map (Appendix C). The bar chart with the aggregate annual data made it easier to see the more frequently reported day of the week, which was either Saturday or Sunday (Figure 23a).

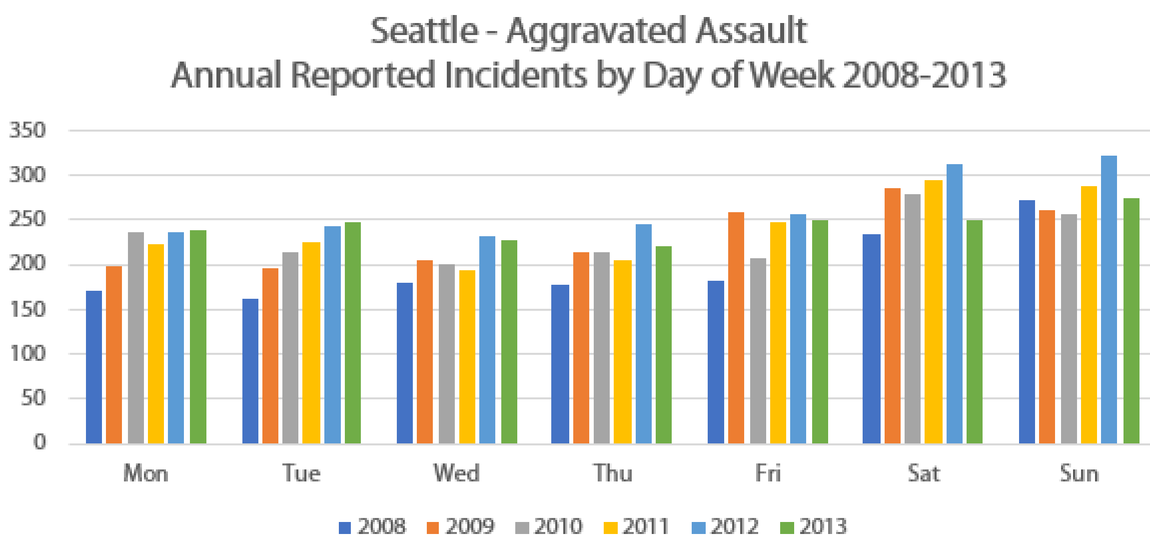

Figure 23a. Day of week: Seattle citywide frequency per year for aggravated assault, 2008-2013.

There is a slight visible pattern of a higher frequency during the warmer summer months of the year. This pattern is much more visible in the monthly heat map (Figure 23b), which also shows that there was both an increase and decrease in the frequency of occurrences across the six-year period.

Seattle - Aggravated Assault
Annual Reported Incidents by Month

	2008	2009	2010	2011	2012	2013
January	108	135	127	131	138	124
February	121	106	100	99	123	129
March	99	103	114	128	133	121
April	95	123	116	125	156	137
May	107	169	157	130	185	163
June	114	147	137	122	183	132
July	143	178	149	163	174	183
August	132	140	171	193	163	160
September	123	172	159	162	179	155
October	118	126	129	153	150	141
November	121	118	114	150	127	124
December	100	102	133	123	137	140

Low High

Figure 23b. Month heatmap: Seattle citywide frequency per year for aggravated assault.

The time-of-day chart (Figure 23c) shows that the most frequently reported time of Assault was between 1801 and 0000.

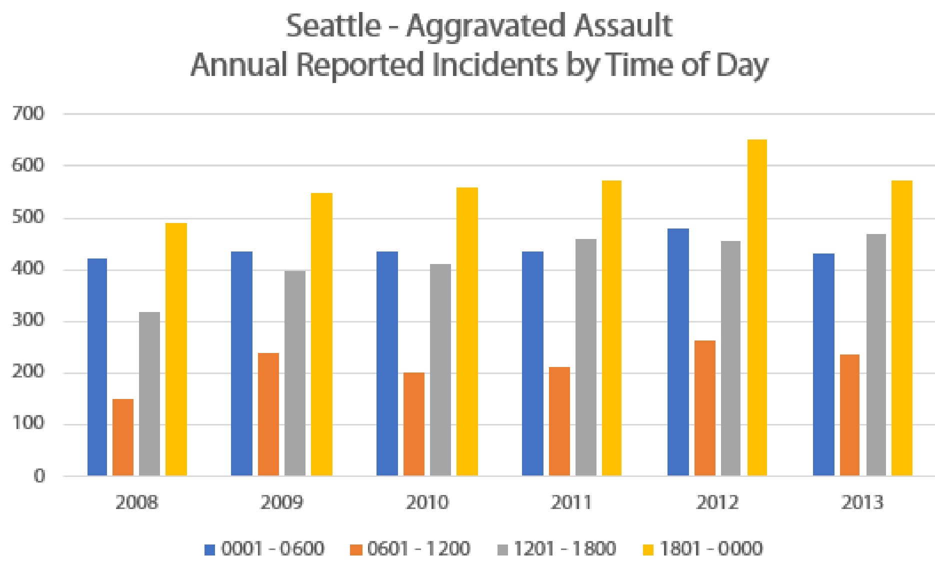

Figure 23c. Time of day: Seattle citywide frequency per year for aggravated assault.

Burglaries were least likely to be reported on the weekends and more likely to be reported on Monday and Tuesday (Appendix C). This was also evident in the bar chart (Figure 23d).

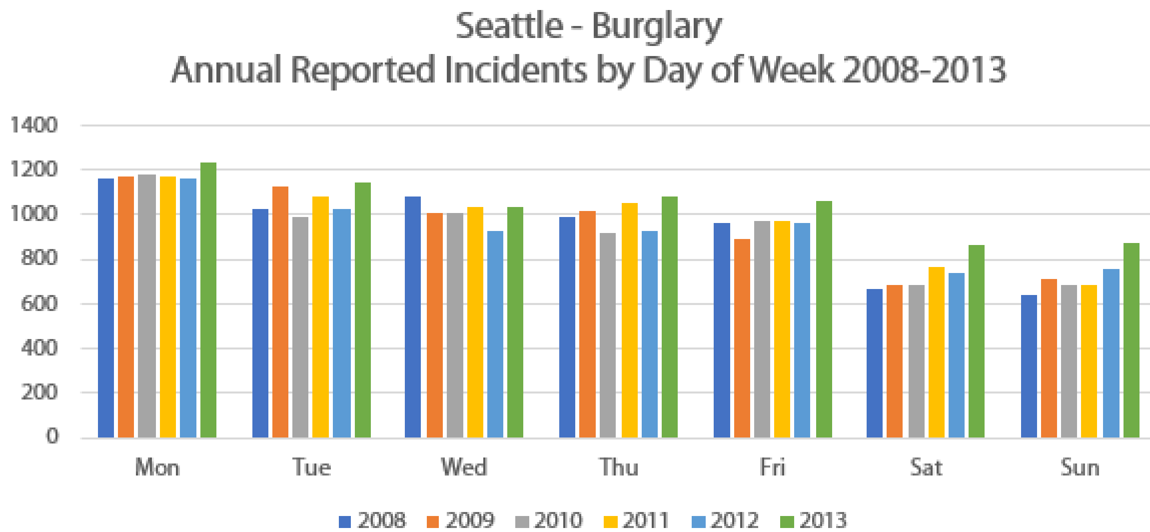

Figure 23d. Day of week: Seattle citywide frequency per year for burglary, 2008-2013.

While there was some higher activity during the summer months, the overall pattern was that burglaries occurred during the colder or winter months (Figure 23e). The frequencies of reported times were between 1201 and 1800 (Figure 23f). There was missing data, however, the patterns (or lack thereof) were not affected.

Seattle - Burglary
Annual Reported Incidents by Month

	2008	2009	2010	2011	2012	2013
January	523	565	658	620	520	660
February	405	438	439	469	473	541
March	462	481	555	537	511	606
April	507	544	458	523	418	604
May	544	469	525	571	481	689
June	607	512	518	490	486	585
July	606	594	477	517	512	566
August	553	631	572	580	539	606
September	621	632	582	560	544	629
October	613	538	551	658	634	624
November	542	603	498	626	715	587
December	545	614	599	608	682	595

Low — High

Figure 23e. Month heatmap: Seattle citywide frequency per year for burglary.

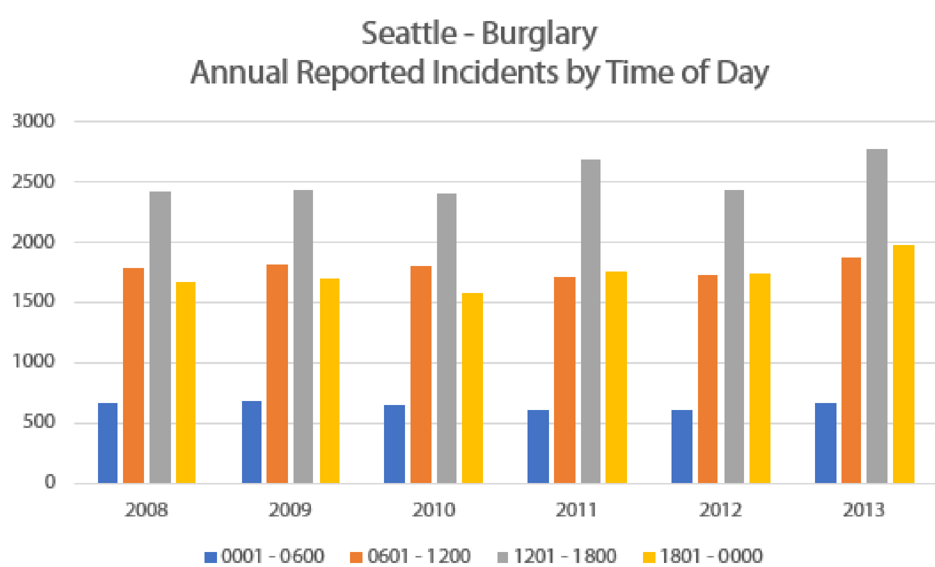

Figure 23f. Time-of-day: Seattle citywide frequency per year for burglary.

Auto Theft appeared to occur less frequently on the weekends, for the most part. The higher reported days fluctuated from year to year, but in general, Monday was the most reported day of the week (Figure 23g).

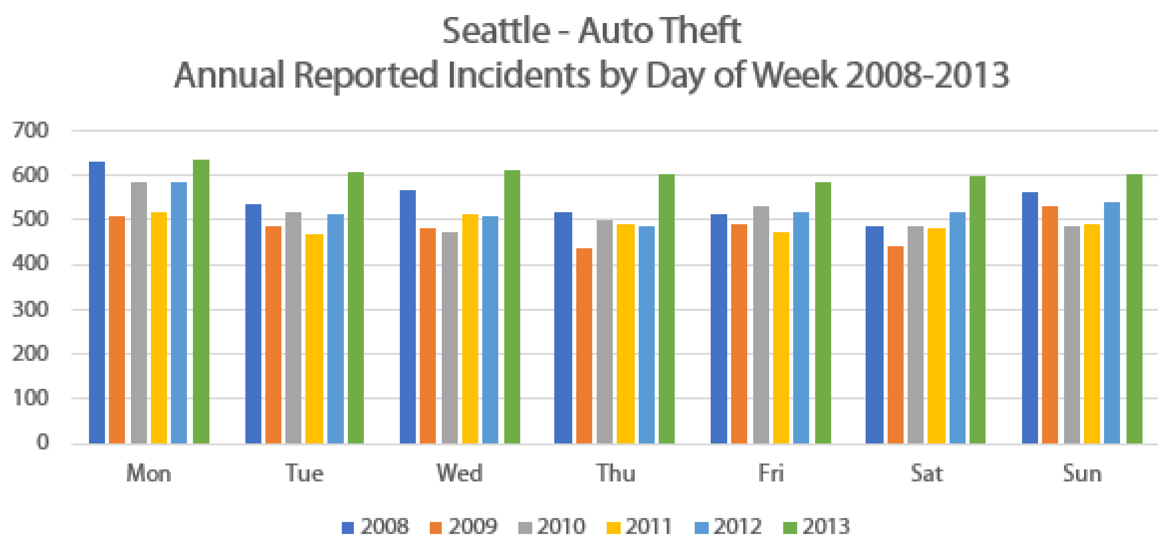

Figure 23g. Day of week: Seattle citywide frequency per year for auto theft, 2008-2013.

Auto Theft had a shifting seasonal trend where there was a high frequency in the fall months for a few years, then it shifted to the winter/spring months and began moving back to the fall months (Figure 23h). This pattern is also visible in the calendar heat map (Appendix C). The most frequently reported time of day was 0601 to 1200 (Figure 23i). An increase in reported events is also visible in 2013.

Seattle - Auto Theft
Annual Reported Incidents by Month

	2008	2009	2010	2011	2012	2013
January	337	277	435	246	279	343
February	382	258	292	209	270	269
March	300	216	325	249	281	283
April	217	191	276	283	268	317
May	260	229	310	325	274	351
June	273	239	368	326	311	347
July	283	291	286	397	346	369
August	343	298	253	319	334	336
September	377	323	264	334	337	438
October	407	329	312	267	334	417
November	378	340	223	239	315	393
December	261	391	240	243	322	383

Low High

Figure 23h. Month heatmap: Seattle citywide frequency per year for auto theft.

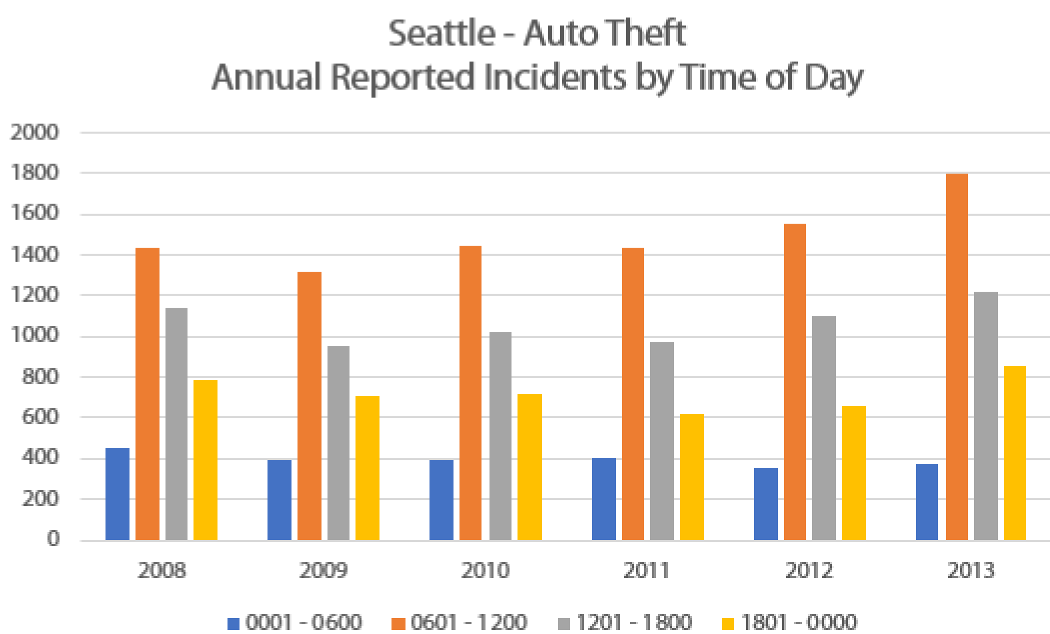

Figure 23i. Time-of-day: Seattle citywide frequency per year for auto theft.

There was no visible pattern with Robbery in viewing the calendar heat map (Appendix C). The bar chart showed a fluctuating pattern for the day of the week (Figure 23j). In 2009 and 2013, Tuesday was the most reported day. In 2011, the highest reported day was Monday.

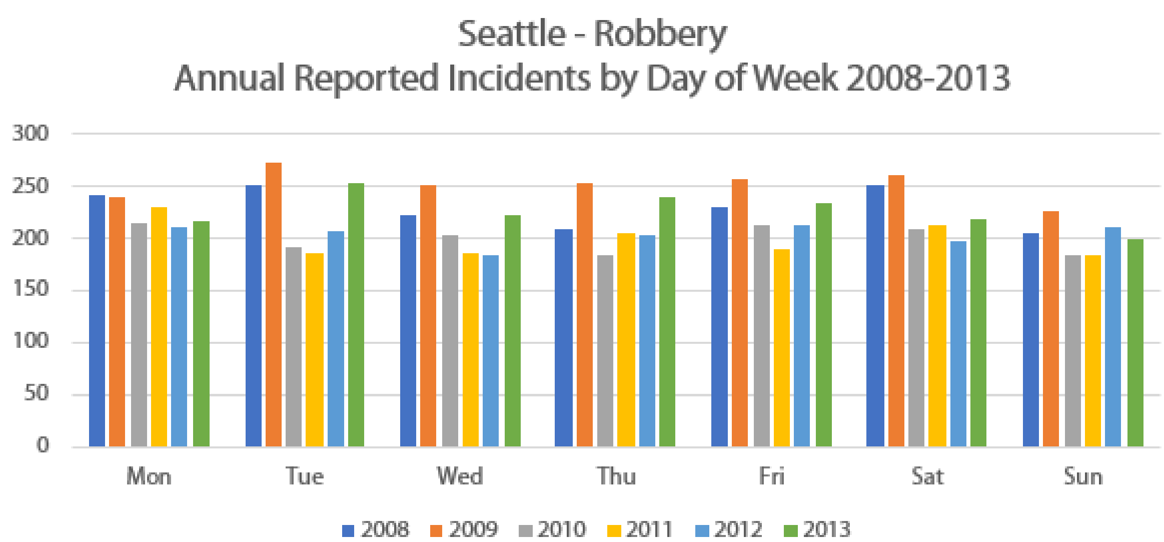

Figure 23j. Day of week: Seattle citywide frequency per year for robbery, 2008-2013.

There was also a fluctuating seasonal pattern in viewing the monthly heat map (Figure 23k). From year to year, it can neither be said that the warmer months nor the colder months were more frequent, rather, it was a mix of the two. The highest frequency of reported times was between 1801 and 0000 (Figure 23l).

Seattle - Robbery
Annual Reported Incidents by Month

	2008	2009	2010	2011	2012	2013
January	101	154	147	111	114	117
February	97	135	100	94	83	130
March	104	136	113	121	116	99
April	147	148	110	109	113	101
May	130	164	125	101	113	133
June	113	155	111	115	123	124
July	127	138	125	118	110	148
August	144	114	123	114	142	156
September	150	163	104	110	139	118
October	178	149	101	142	137	159
November	178	147	109	118	116	169
December	138	156	129	143	115	126

Low High

Figure 23k. Month heatmap: Seattle citywide frequency per year for robbery

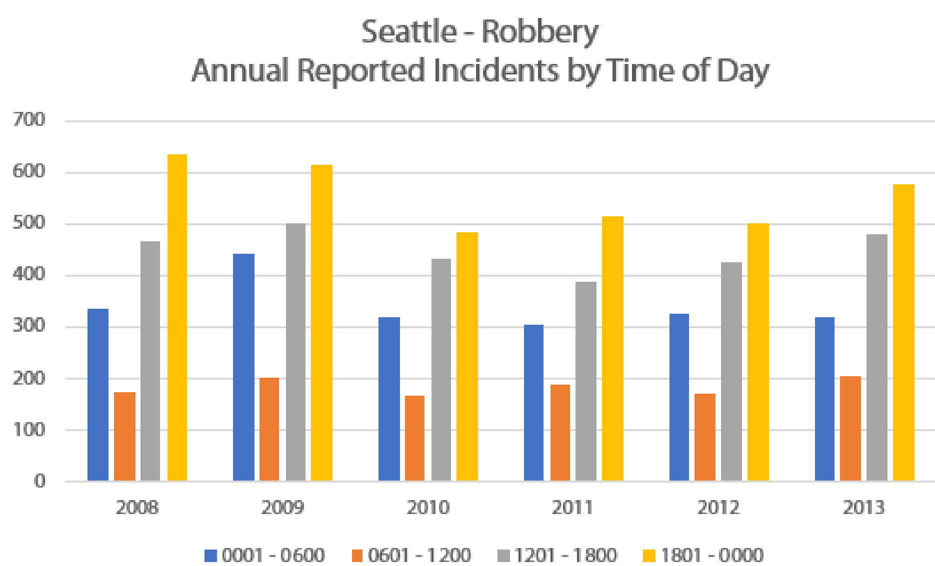

Figure 23l. Time-of-day: Seattle citywide frequency per year for robbery

Assaults and Burglary had the most distinguishable monthly and daily patterns. For the time of day, all the crime types presented a clear pattern in the bar charts.

5.5.3 Chicago

There was a clear pattern with Assault, which had higher reporting during the warmer months of May, June, July, and August, and more frequently on the weekends (Appendix C). The aggregated annual data in the bar chart also showed that Saturday and Sunday were the highest reported days of the week (Figures 24a-b).

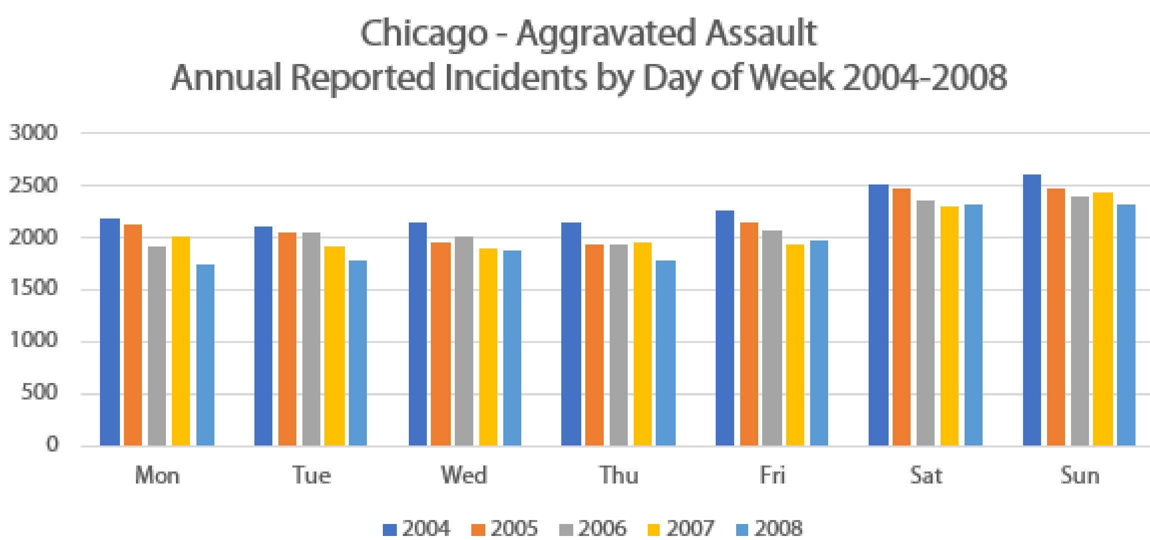

Figure 24a. Day of week: Chicago citywide frequency per year for aggravated assault, 2004-2008.

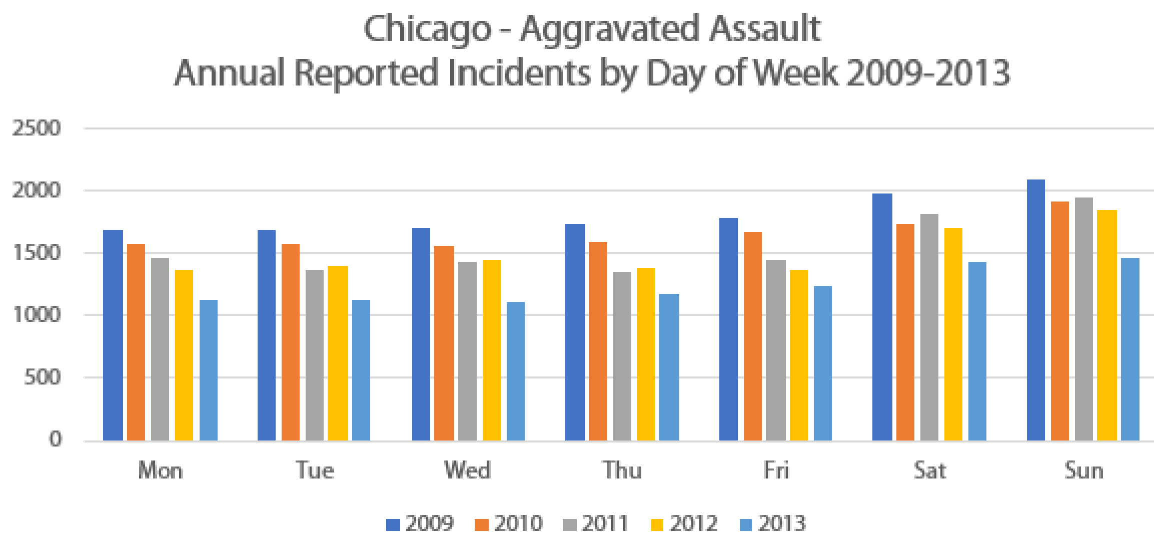

Figure 24b. Day of week: Chicago citywide frequency per year for aggravated assault, 2009-2013.

In viewing the monthly heat map (Figure 24c), it is clear there was a decrease in the frequency of assaults over the 10-year period. Assaults were more frequently reported between the hours of 1801 and 0000 (Figure 24d).

Chicago - Aggravated Assault
Annual Reported Incidents by Month

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
January	931	873	1063	871	882	780	710	667	626	630
February	1025	916	806	667	754	762	688	564	574	506
March	1326	1146	1124	1190	1059	1112	976	843	926	661
April	1348	1421	1280	1200	1251	1125	1085	976	787	704
May	1569	1500	1458	1352	1320	1232	1167	1059	1010	813
June	1673	1618	1441	1502	1413	1316	1149	1117	1123	894
July	1655	1649	1649	1494	1474	1270	1208	1232	1146	912
August	1500	1497	1415	1396	1492	1296	1137	1023	1064	941
September	1497	1299	1285	1445	1286	1150	1060	903	912	743
October	1377	1302	1233	1403	1244	997	1045	988	882	743
November	1127	1068	1029	1021	870	909	791	722	751	567
December	928	822	931	882	706	710	624	733	713	563

Low High

Figure 24c. Month heatmap: Chicago citywide frequency per year for aggravated assault.

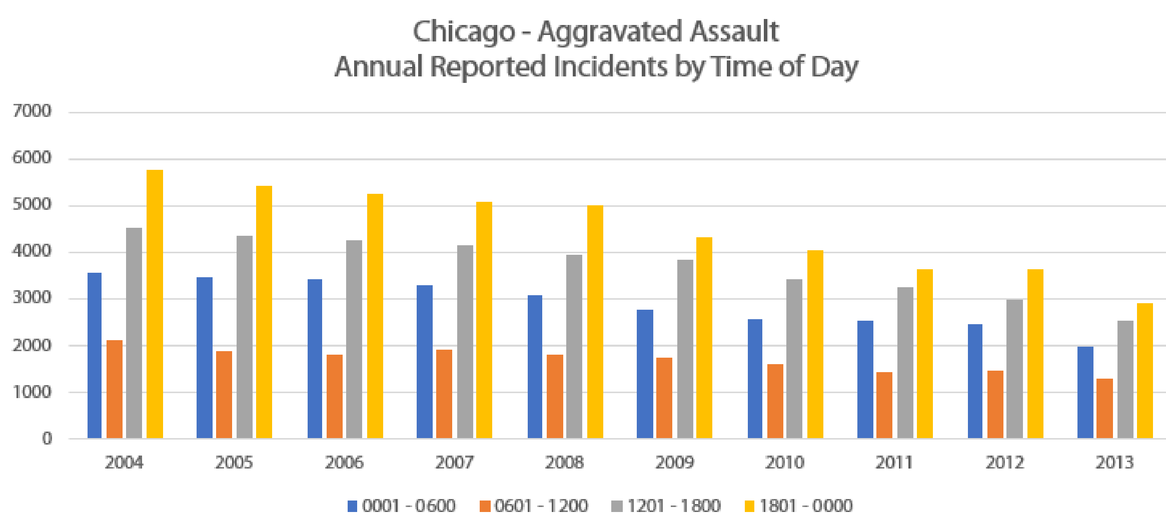

Figure 24d. Time-of-day: Chicago citywide frequency per year for aggravated assault.

Burglary was least likely to occur on the weekends (Appendix C). The aggregated annual data in the bar chart also showed that Saturday and Sunday were the lowest reported days of the week (Figures 24e-f). Additionally, Friday was the highest reported day for all years, except 2008.

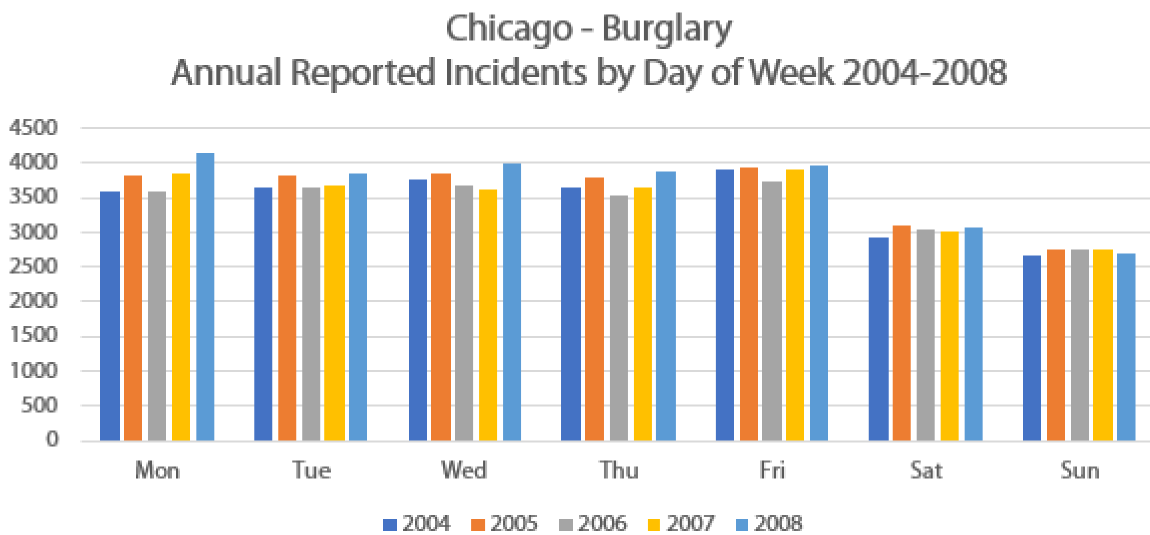

Figure 24e. Day of week: Chicago citywide frequency per year for burglary, 2004-2008.

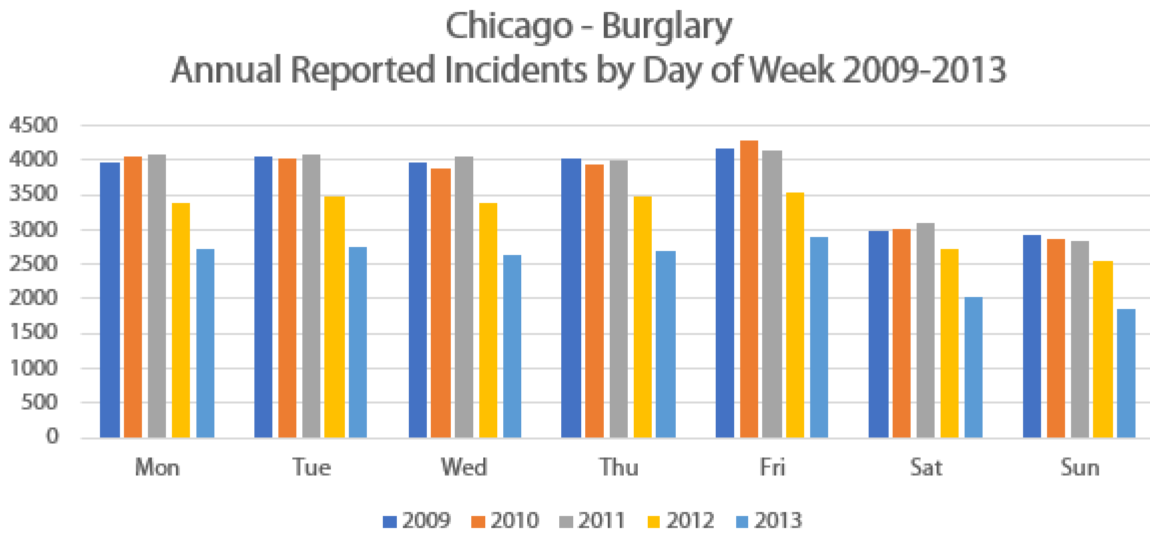

Figure 24f. Day of week: Chicago citywide frequency per year for burglary, 2009-2013.

The pattern of the higher reporting frequency was during the warmer summer months of the year (Figure 24g). Burglaries briefly increased, then decreased over the 10-year period. The most frequently reported time of day was between 0601 and 1200 (Figure 24h).

Chicago - Burglary
Annual Reported Incidents by Month

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
January	1727	1781	1985	1826	1853	1726	1932	1932	1730	1556
February	1551	1470	1561	1317	1516	1507	1461	1403	1379	1151
March	1845	1750	1849	1716	1715	1861	1970	1821	1617	1230
April	1844	1947	1682	1840	1877	2021	1972	2017	1624	1347
May	1994	2159	2157	2204	2206	2163	2223	2429	1889	1550
June	2098	2229	1961	2149	2114	2297	2219	2386	2041	1457
July	2289	2344	2227	2230	2531	2462	2295	2369	2248	1542
August	2241	2447	2204	2348	2339	2579	2681	2587	2194	1749
September	2206	2410	2079	2219	2437	2472	2411	2480	1969	1611
October	2136	2422	2244	2348	2579	2402	2455	2426	2104	1581
November	2166	2167	1972	2293	2279	2363	2343	2266	1956	1453
December	2074	1910	2058	1997	2174	2261	2094	2160	1787	1367

Low High

Figure 24g. Month heatmap: Chicago citywide frequency per year for burglary.

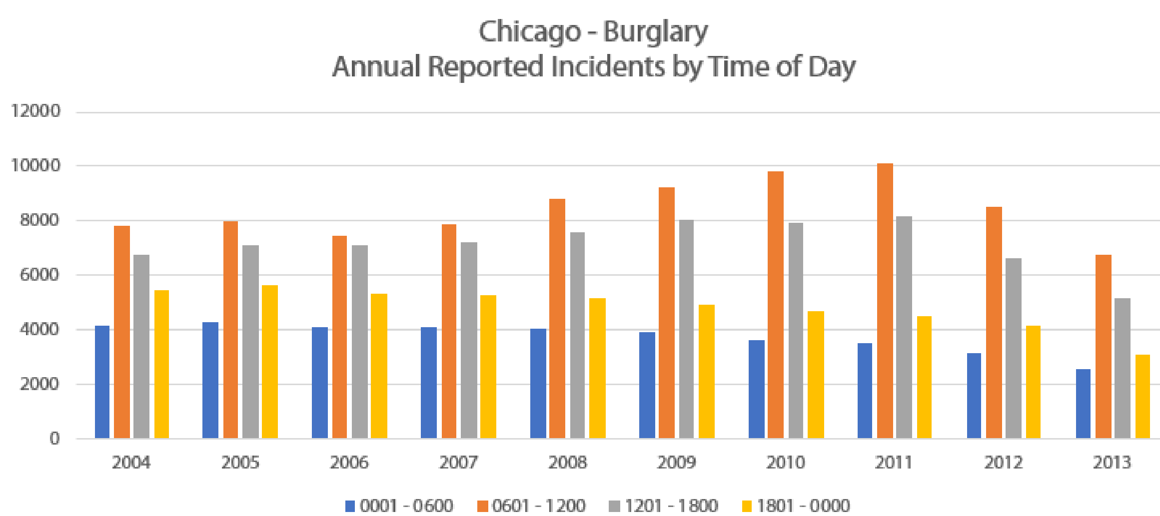

Figure 24h. Time-of-day: Chicago citywide frequency per year for burglary.

In the calendar heat maps, Auto Theft did not have a discernable trend (Appendix C). The aggregated annual data in the bar chart showed that Friday was generally the highest reported day of the week (Figures 24i-j).

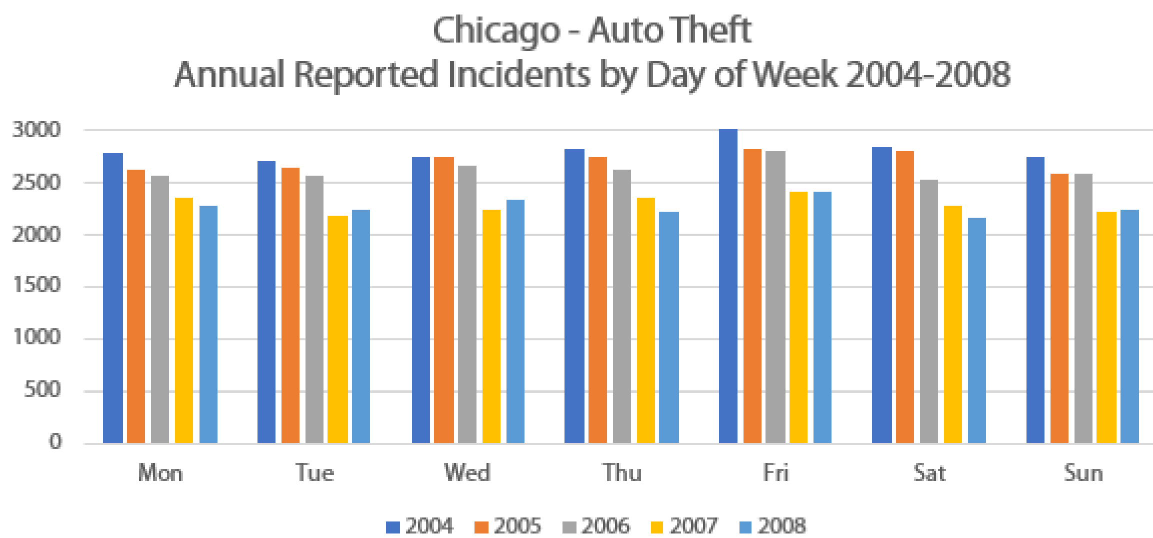

Figure 24i. Day of week: Chicago citywide frequency per year for auto theft, 2004-2008.

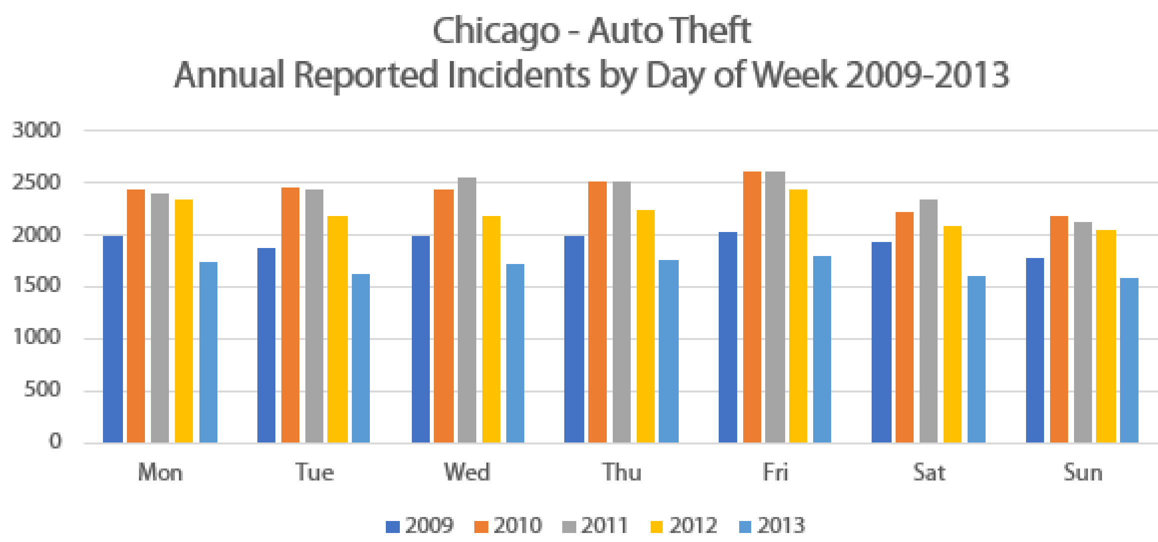

Figure 24j. Day of week: Chicago citywide frequency per year for auto theft, 2009-2013.

The monthly heatmap showed that after a brief increase in 2010, there was an overall decreased (Figure 24k) in auto thefts. This crime type was more frequently reported between the hours of 1801 and 0000 (Figure 24l).

Chicago - Auto Theft
Annual Reported Incidents by Month

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
January	1517	1507	1801	1376	1269	1099	1380	1625	1367	1415
February	1455	1361	1478	1139	1060	1024	965	1124	1086	1206
March	1666	1637	1573	1320	1398	1094	1215	1458	1288	1044
April	1648	1515	1425	1271	1244	995	1251	1489	1256	862
May	1691	1629	1637	1382	1239	984	1507	1557	1350	887
June	1702	1567	1624	1359	1386	1016	1331	1571	1353	977
July	1775	1497	1573	1359	1665	1129	1373	1500	1271	959
August	1670	1548	1636	1449	1607	1146	1447	1337	1259	951
September	1617	1533	1425	1293	1407	1157	1551	1235	1219	867
October	1653	1818	1440	1485	1276	1271	1582	1316	1310	853
November	1610	1619	1344	1257	1150	1275	1544	1358	1362	832
December	1647	1704	1368	1336	1163	1366	1702	1364	1363	945

Low High

Figure 24k. Month heatmap: Chicago citywide frequency per year for auto theft.

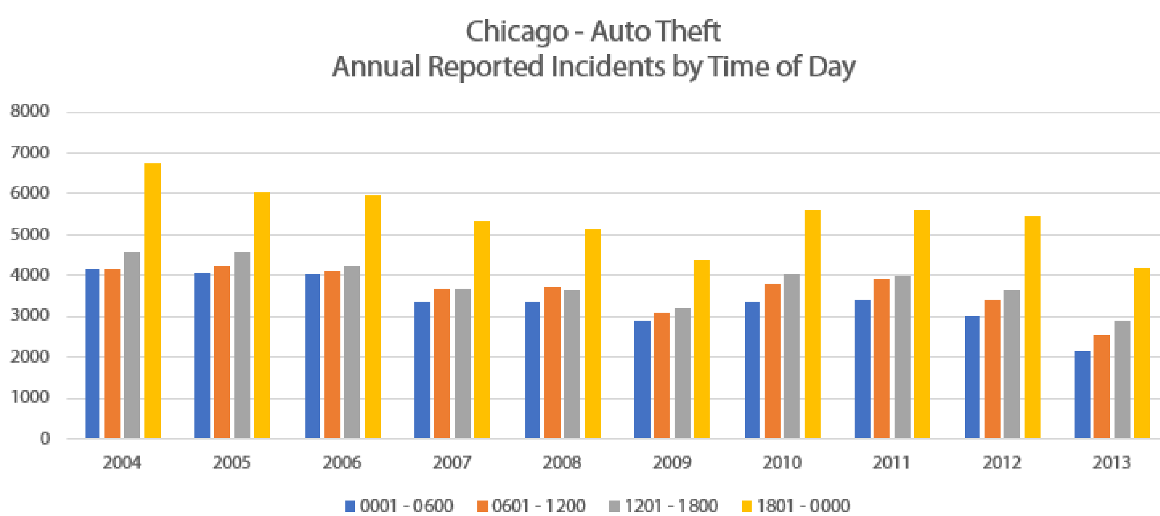

Figure 24l. Time-of-day: Chicago citywide frequency per year for auto theft.

It appeared as though Friday was the day with more reported robbery incidents in the calendar heatmaps (Appendix C). The aggregated data in the bar chart showed that the highest reported day of the week was generally Friday (Figures 24m-n).

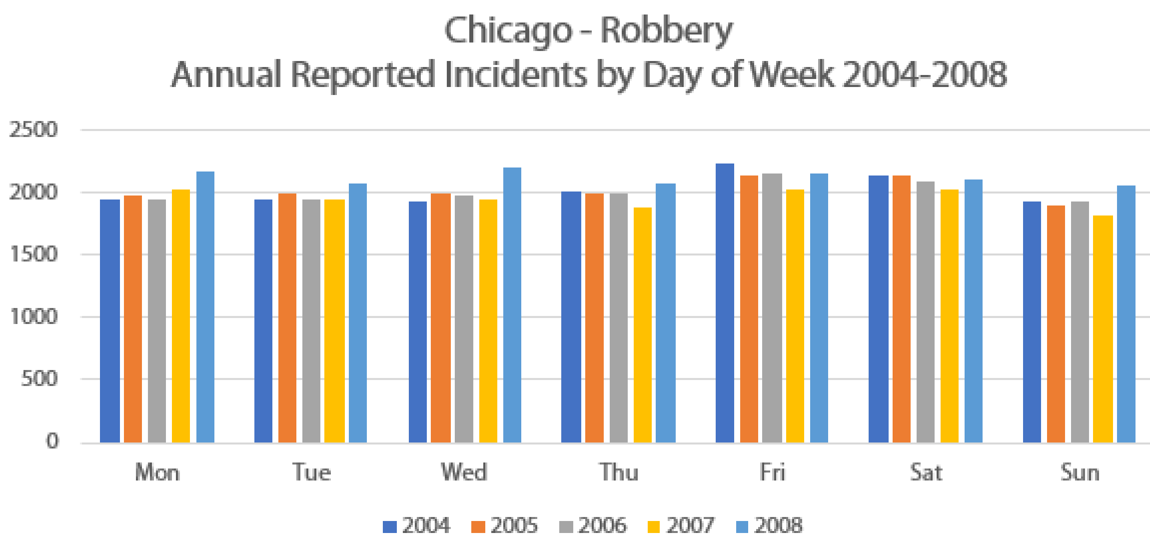

Figure 24m. Day of week: Chicago citywide frequency per year for robbery, 2004-2008.

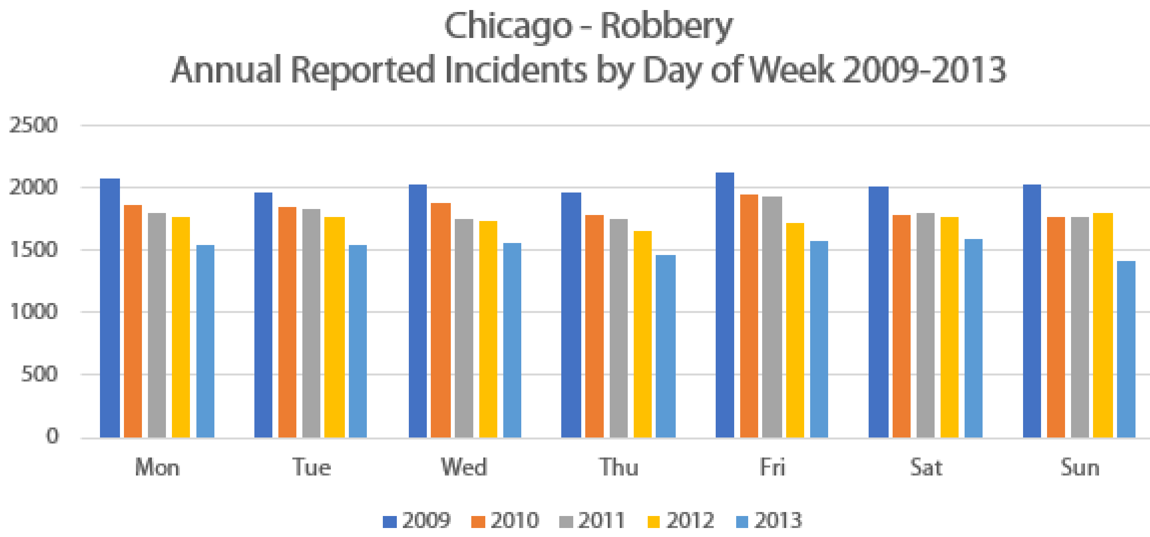

Figure 24n. Day of week: Chicago citywide frequency per year for robbery, 2009-2013.

Robbery was least likely to occur during the winter and early spring months and the frequency of reported robberies decreased over the 10-year period (Figure 24o). Robbery was more frequently reported between the hours of 1801 and 0000 (Figure 24p).

Chicago - Robbery
Annual Reported Incidents by Month

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
January	1131	1021	1150	997	1130	1100	1099	999	893	985
February	907	846	906	692	848	865	647	677	621	645
March	1052	976	998	934	1100	1061	909	866	754	703
April	1000	1054	1054	986	1065	1094	1032	898	873	761
May	1231	1074	1151	1177	1203	1264	1074	1152	1138	879
June	1203	1245	1177	1193	1209	1242	1102	1062	1194	905
July	1329	1416	1301	1330	1317	1438	1190	1157	1248	1151
August	1240	1378	1305	1266	1389	1319	1192	1204	1139	1036
September	1286	1297	1211	1229	1465	1210	1131	1153	1061	968
October	1347	1306	1386	1307	1517	1203	1337	1267	1131	908
November	1199	1275	1204	1334	1331	1197	1121	1094	1085	834
December	1217	1252	1211	1237	1248	1203	1039	1115	1081	924

Low High

Figure 24o. Month heatmap: Chicago citywide frequency per year for robbery.

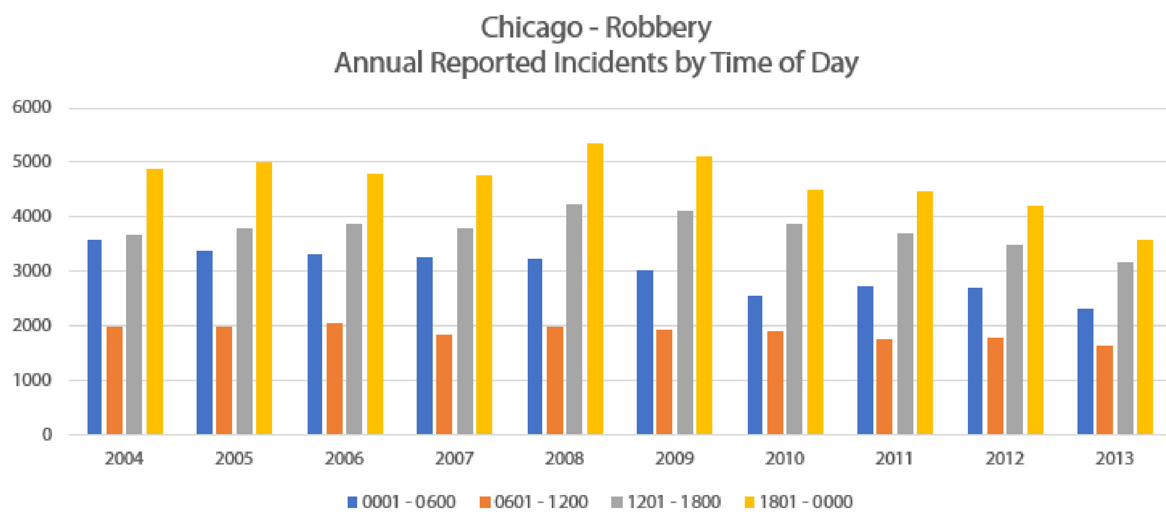

Figure 24p. Time-of-day: Chicago citywide frequency per year for robbery.

Overall, Chicago's seasonal patterns were similar to Atlanta and Seattle, especially with Auto Theft and Robbery.

5.6 Focus Areas

The choropleth maps were helpful with identifying neighborhood areas with persistent higher crime rates, however, smaller areas with institutionalized clustering of crime could not be easily identified; therefore, point density maps and a grid mapping method were used to identify those locations with persistent high crime. Additionally, for the point density maps, each city was compared to itself year over year due to the high number of crime incidents per quarter mile in Chicago.

As each city had more than one grid with high-density crime events across the 10-year period (6 years for Seattle), the grid with the most consistent high-level crime using a discrete data count was selected to represent the focus area.

5.6.1 Atlanta

The point density maps for Atlanta showed that crime was concentrated towards the central eastern part of the city (Figures 25a-c). The neighborhood boundary overlay was for location reference.

The highest densities were mainly concentrated throughout the central and south of the city. A several of the high-density locations disappeared after a few years. That was not due to any sort of policing action but had to do with the demolition of public housing buildings.

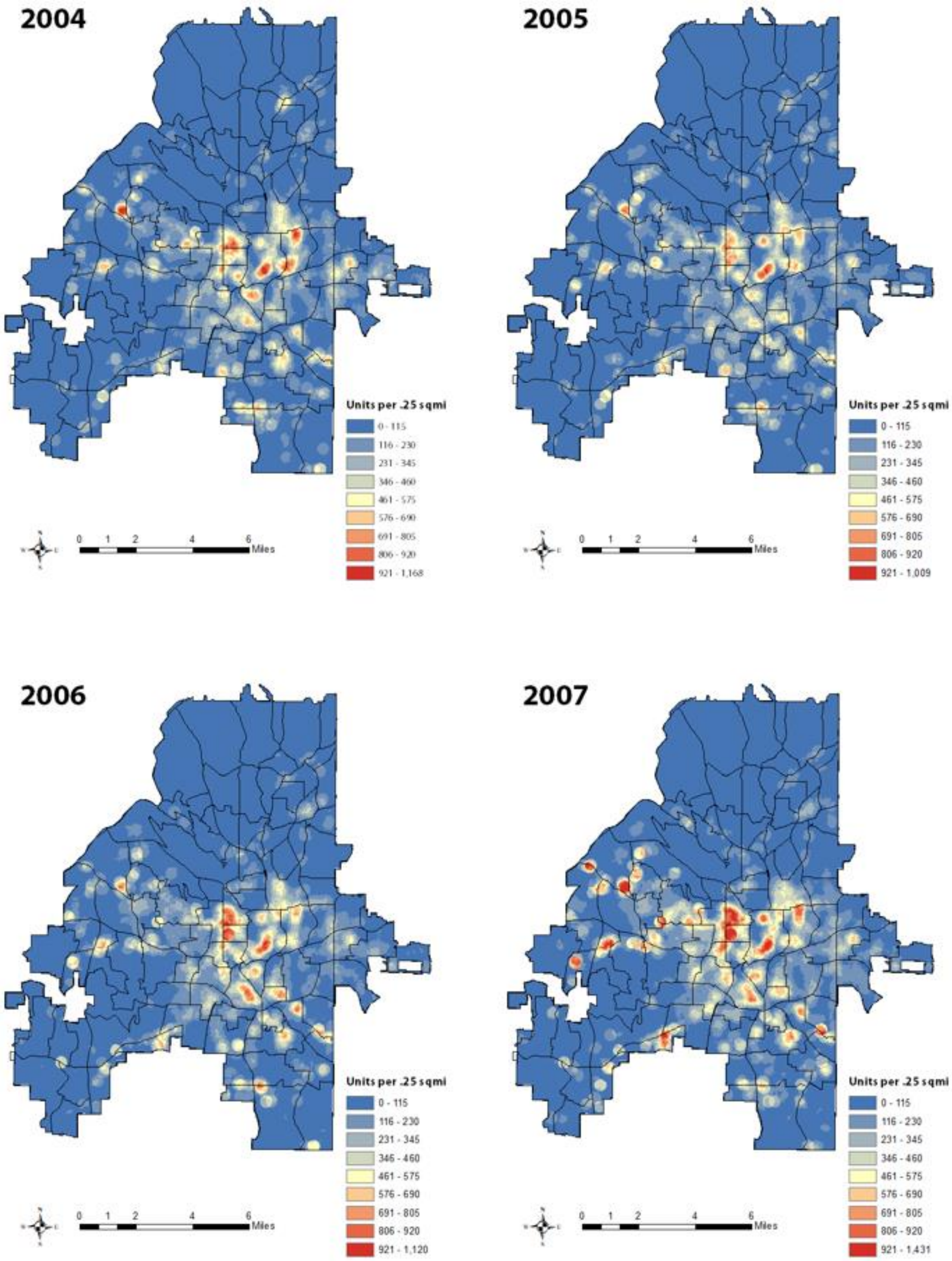

Figure 25a. Atlanta point density maps showing concentration of crime, 2004-2007.

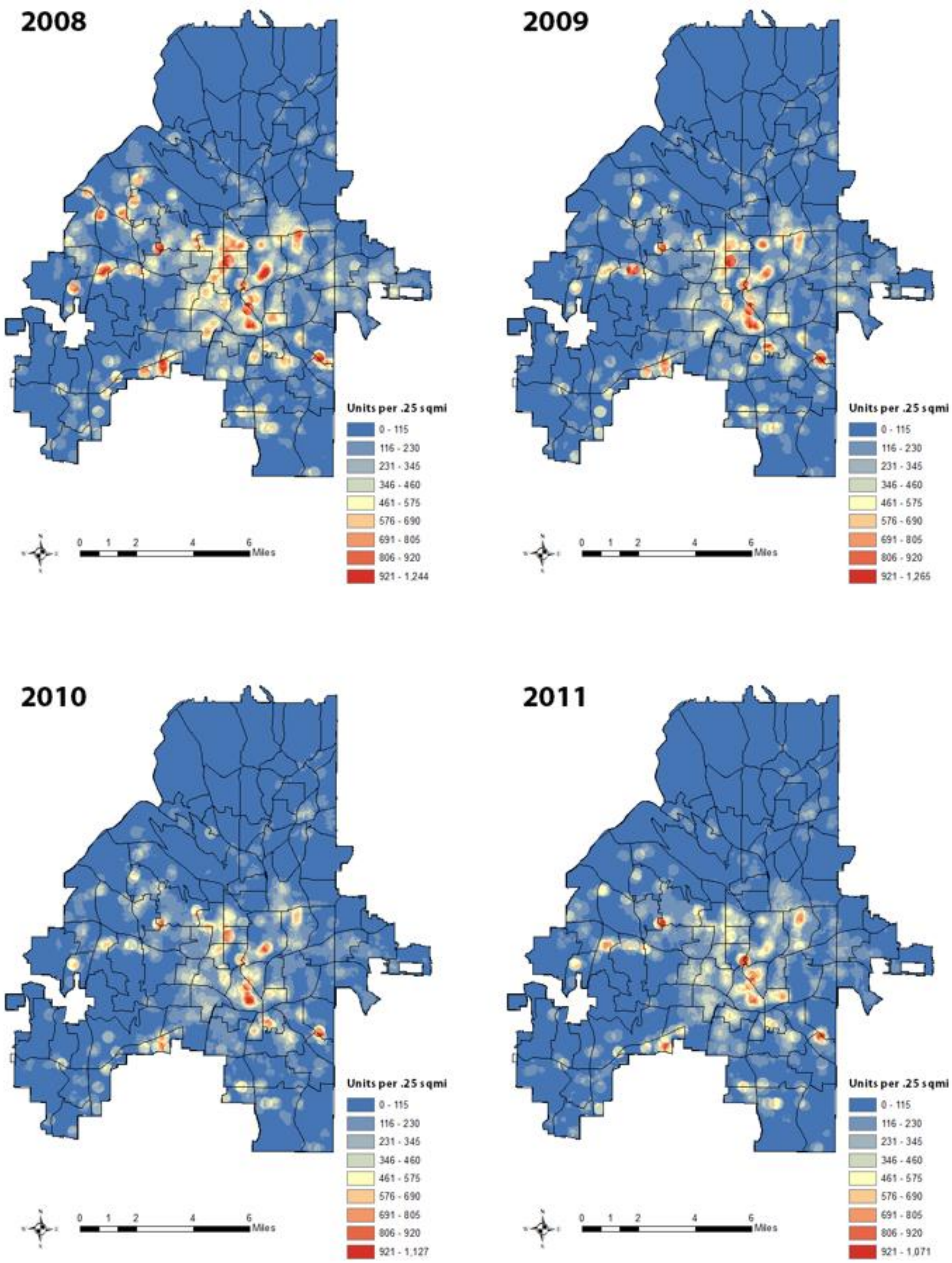

Figure 25b. Atlanta point density maps showing concentration of crime, 2008-2011.

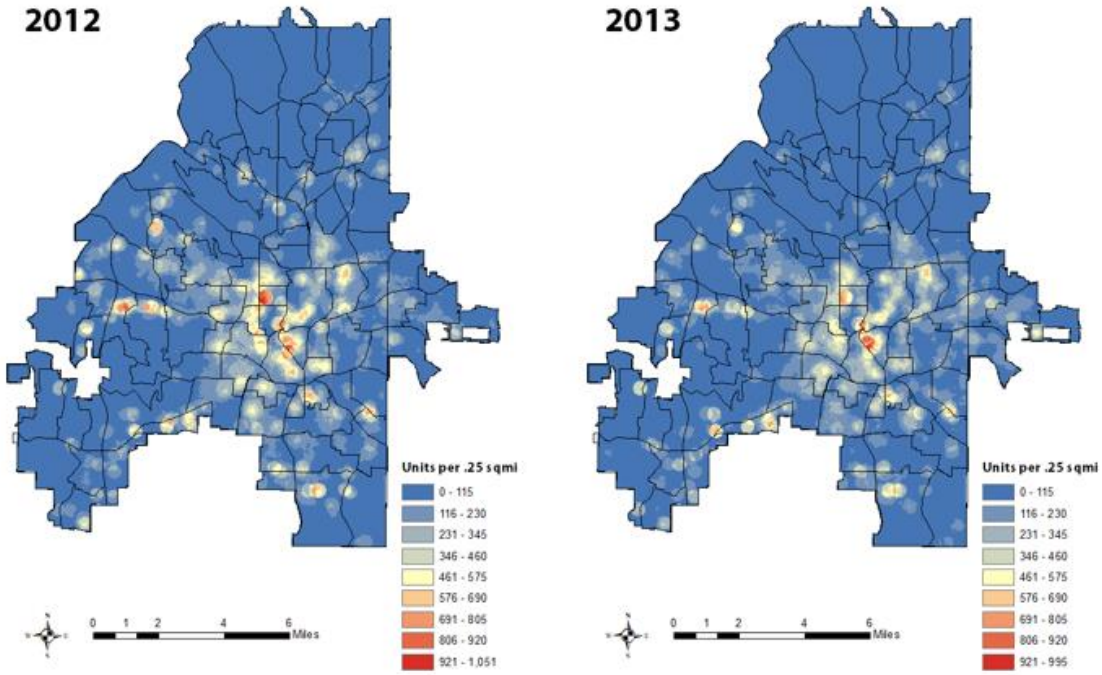

Figure 25c. Atlanta point density maps showing concentration of crime, 2012-2013.

When examining the gridded maps (Figures 24d-f), there were several high frequency grids in the central-eastern part of the city with a few outlier grids to the northeast, west and south of the city. The grids in the central-eastern part of the city closely align with the point density maps, identifying the Downtown neighborhood.

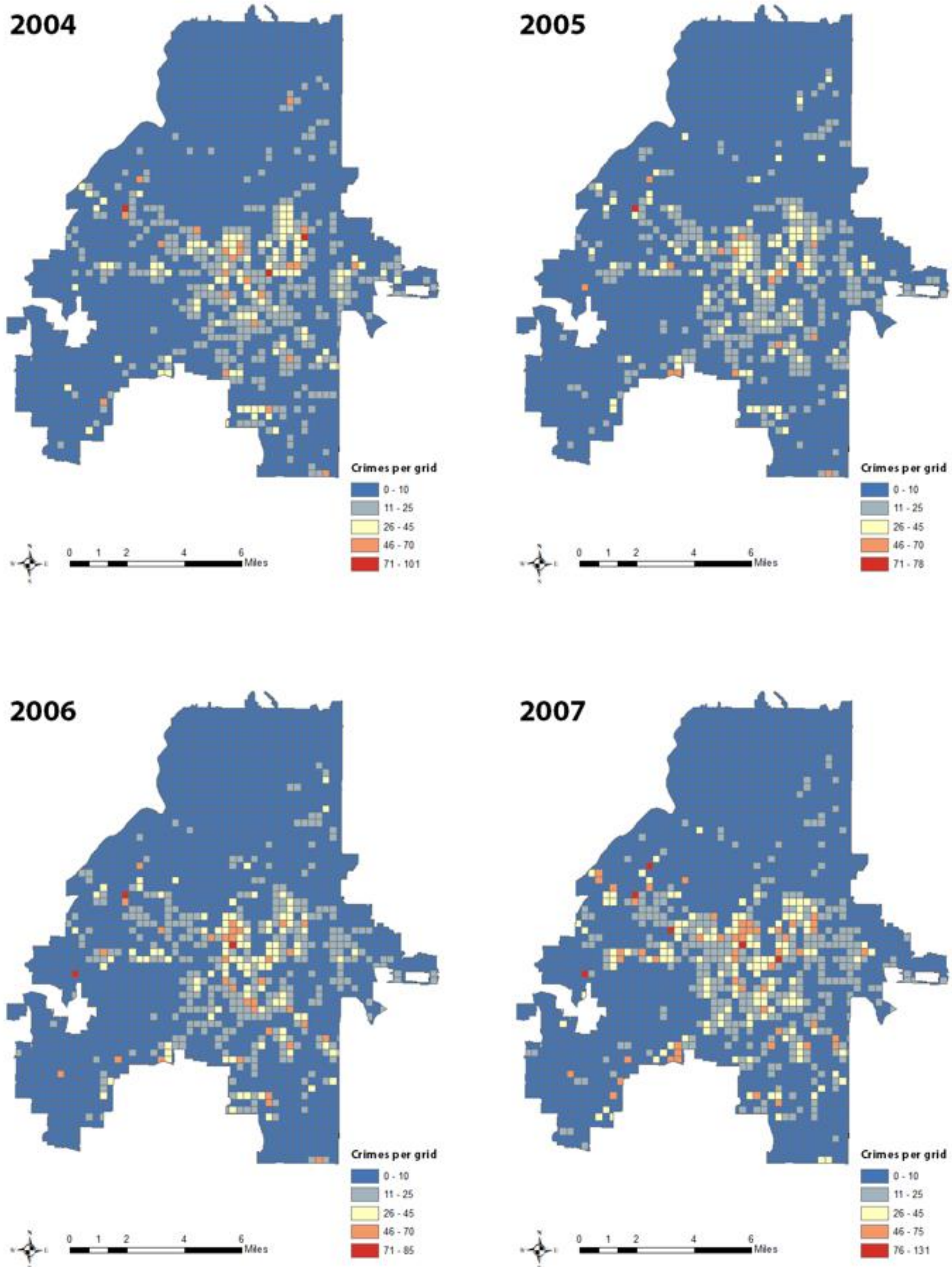

Figure 25d. Atlanta grid comparison of crime per 1320ft square grid, 2004-2007.

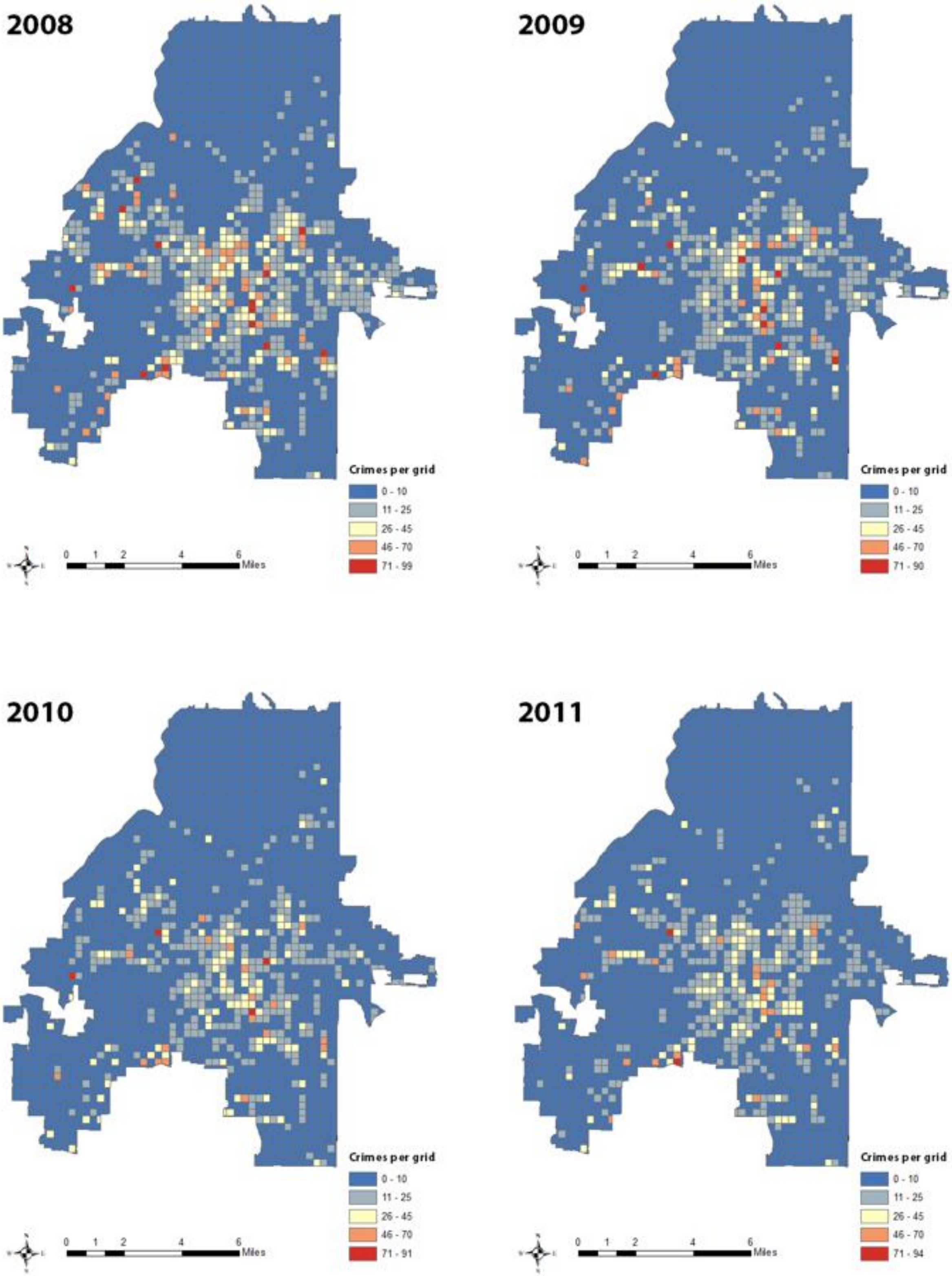

Figure 25e. Atlanta grid comparison of crime per 1320ft square grid, 2008-2011.

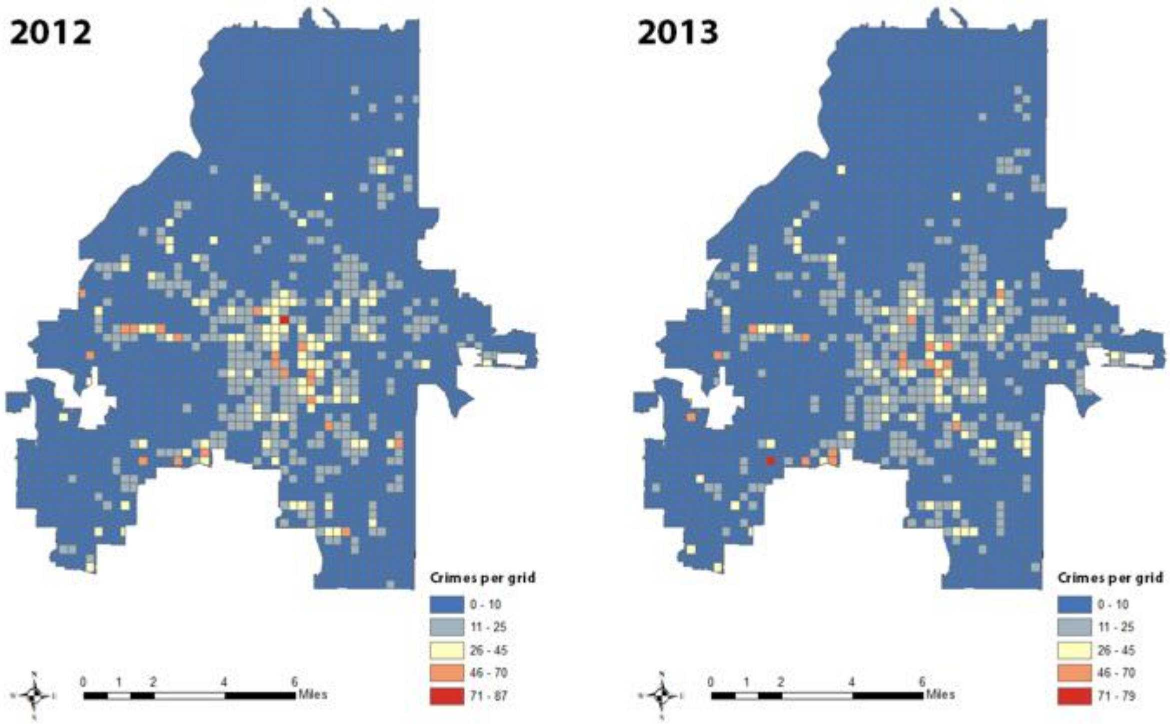

Figure 25f. Atlanta grid comparison of crime per 1320ft square grid, 2012-2013.

For Atlanta, the Castleberry Hill/Downtown neighborhood area (Figure 25g) contained the grid with the most consistent high-level crime. The grid identified was in the Downtown Business District (Figure 25h).

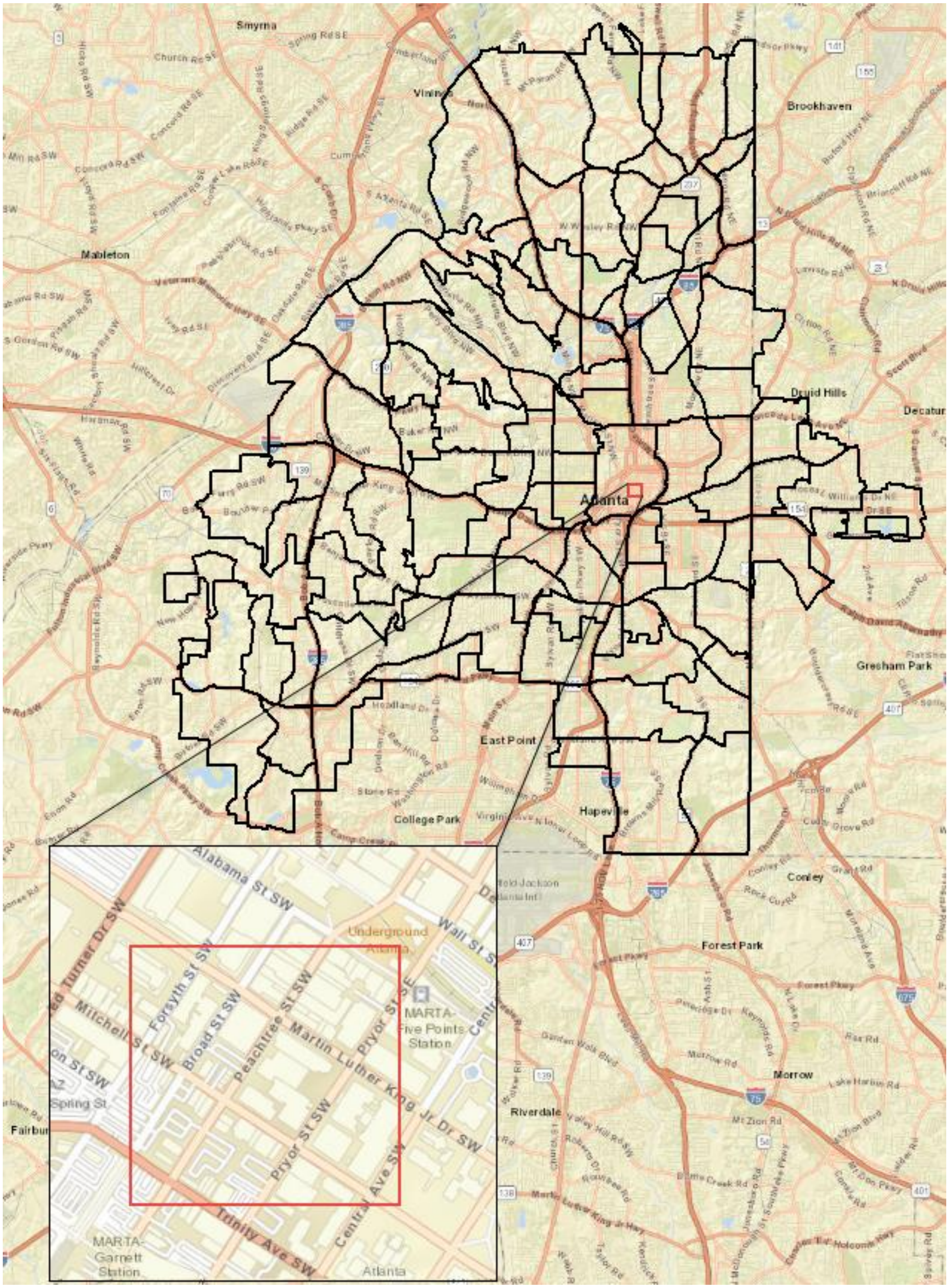

Figure 25g. Atlanta, GA with focus area referenced.

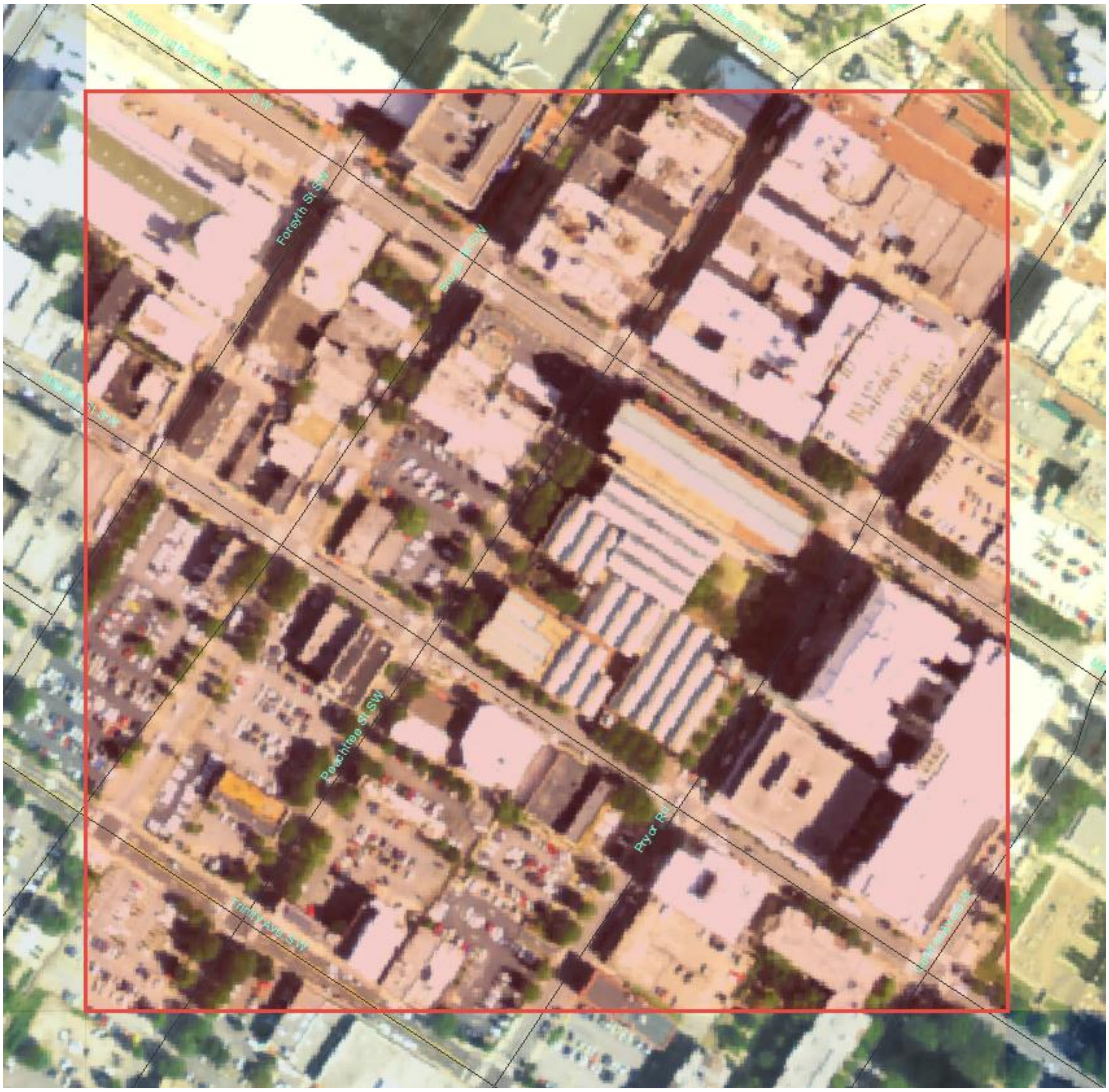

Figure 25h. Atlanta focus area – Downtown business district.

5.6.2 Seattle

In Seattle, the highest density location was also the highest frequency location. It was in the larger community area of Downtown (Figures 26a), within the Central Business District, where Pike Place Market was located (Figures 26b).

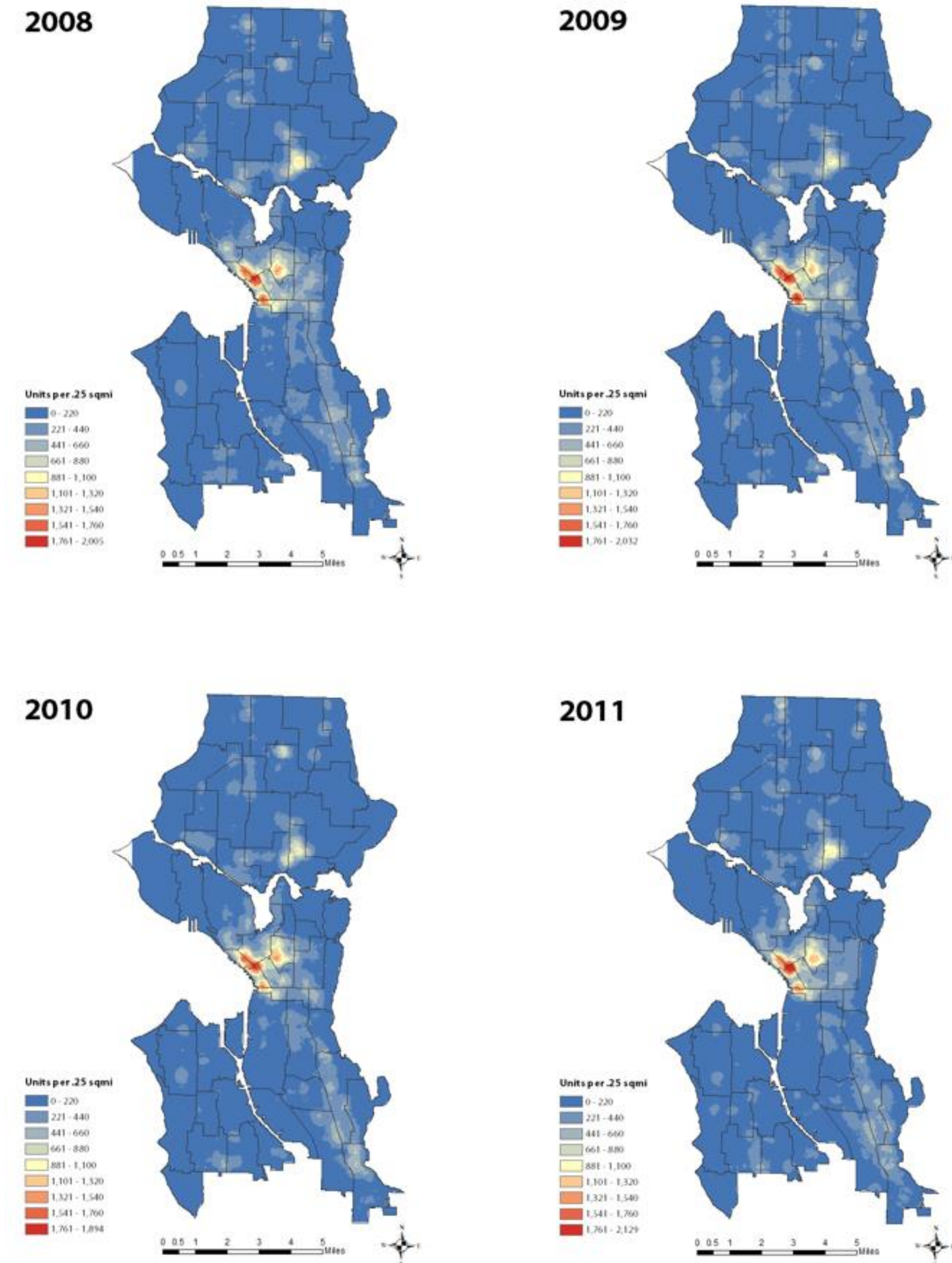

Figure 26a. Seattle point density maps showing concentration of crime, 2008-2011.

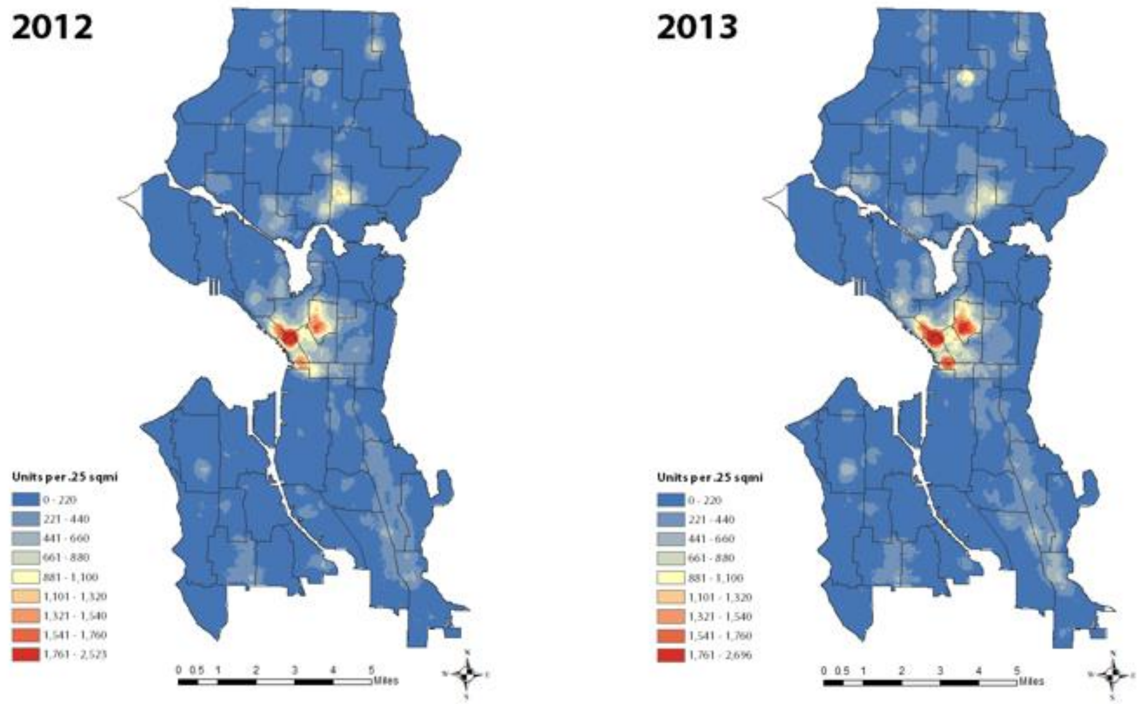

Figure 26b. Seattle point density maps showing concentration of crime, 2012-2013.

When examining the grid maps for Seattle (Figures 26c-d), there were a few high frequency locations towards the north of the city. Overall, the grids aligned with the point density maps in identifying the Downtown Central Business District neighborhood as the high-frequency area (Figures 26e-f).

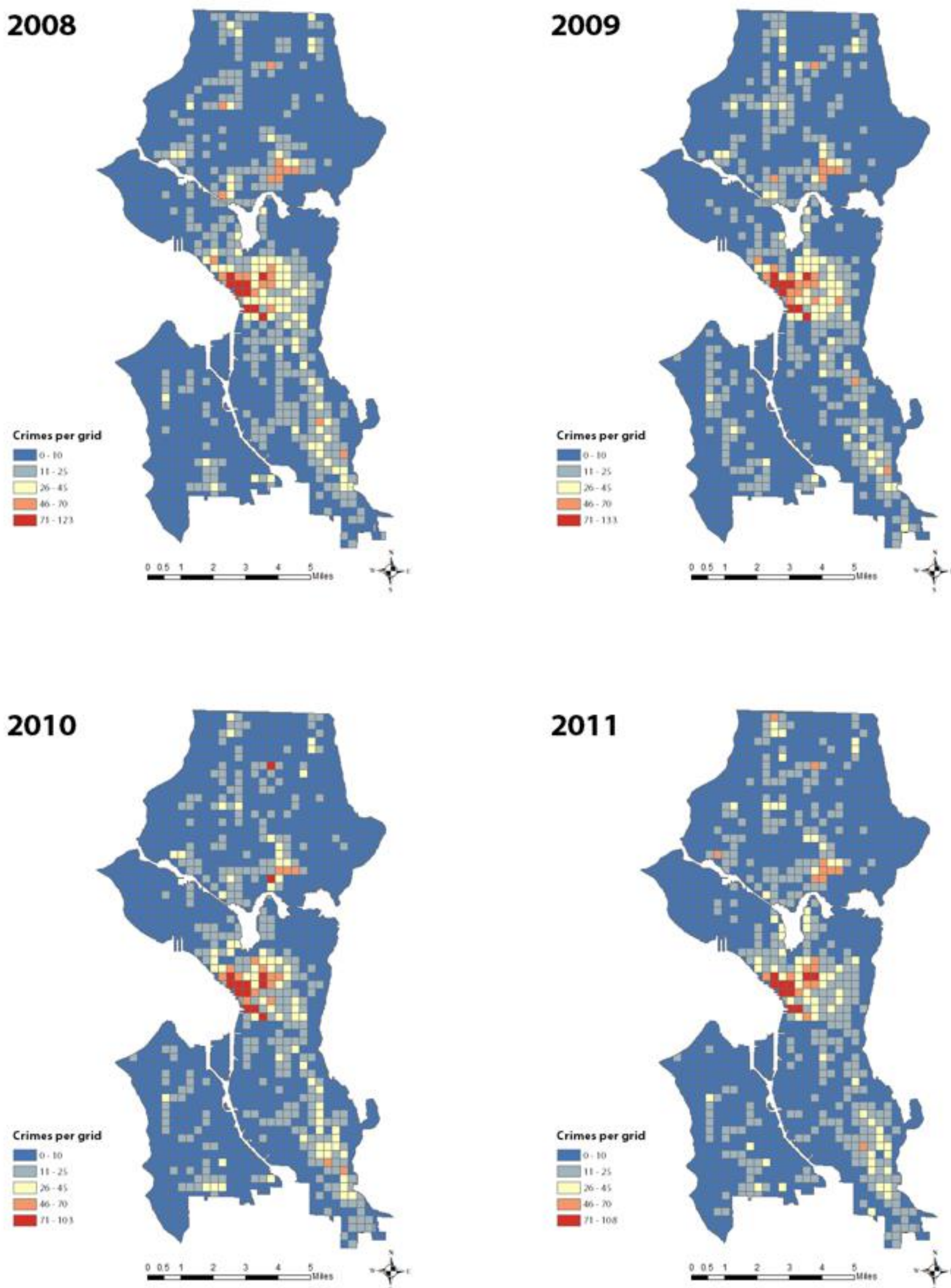

Figure 26c. Seattle grid comparison of crime per 1320ft square grid, 2008-2011.

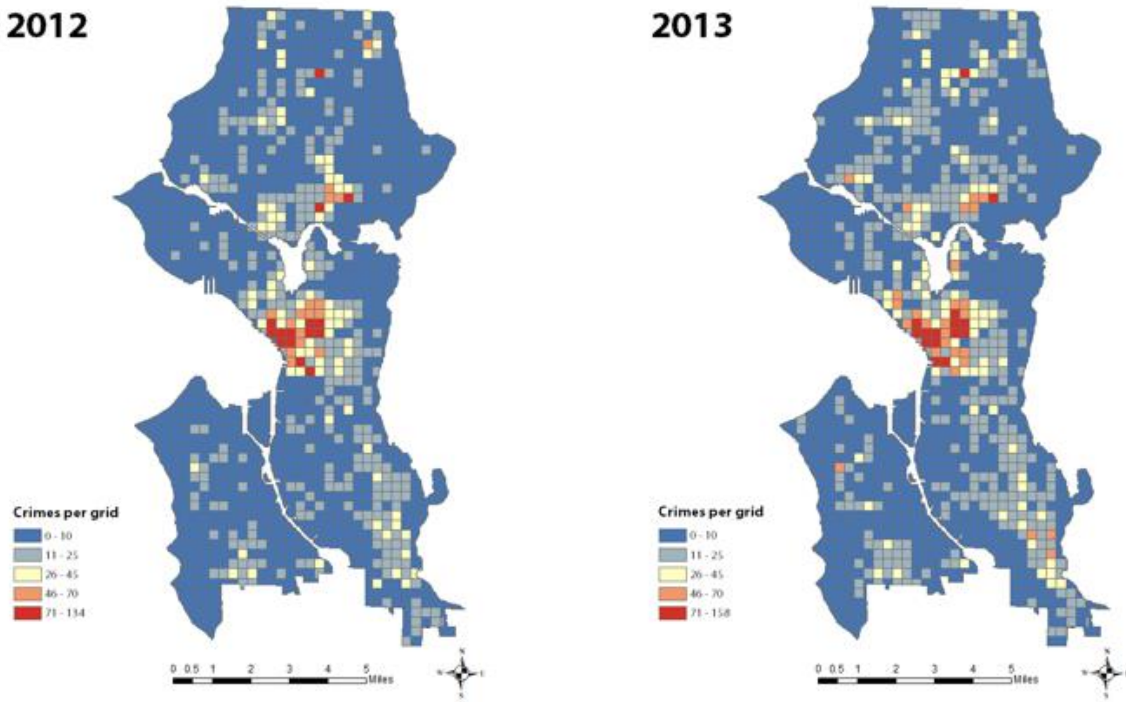

Figure 26d. Seattle grid comparison of crime per 1320ft square grid, 2012-2013.

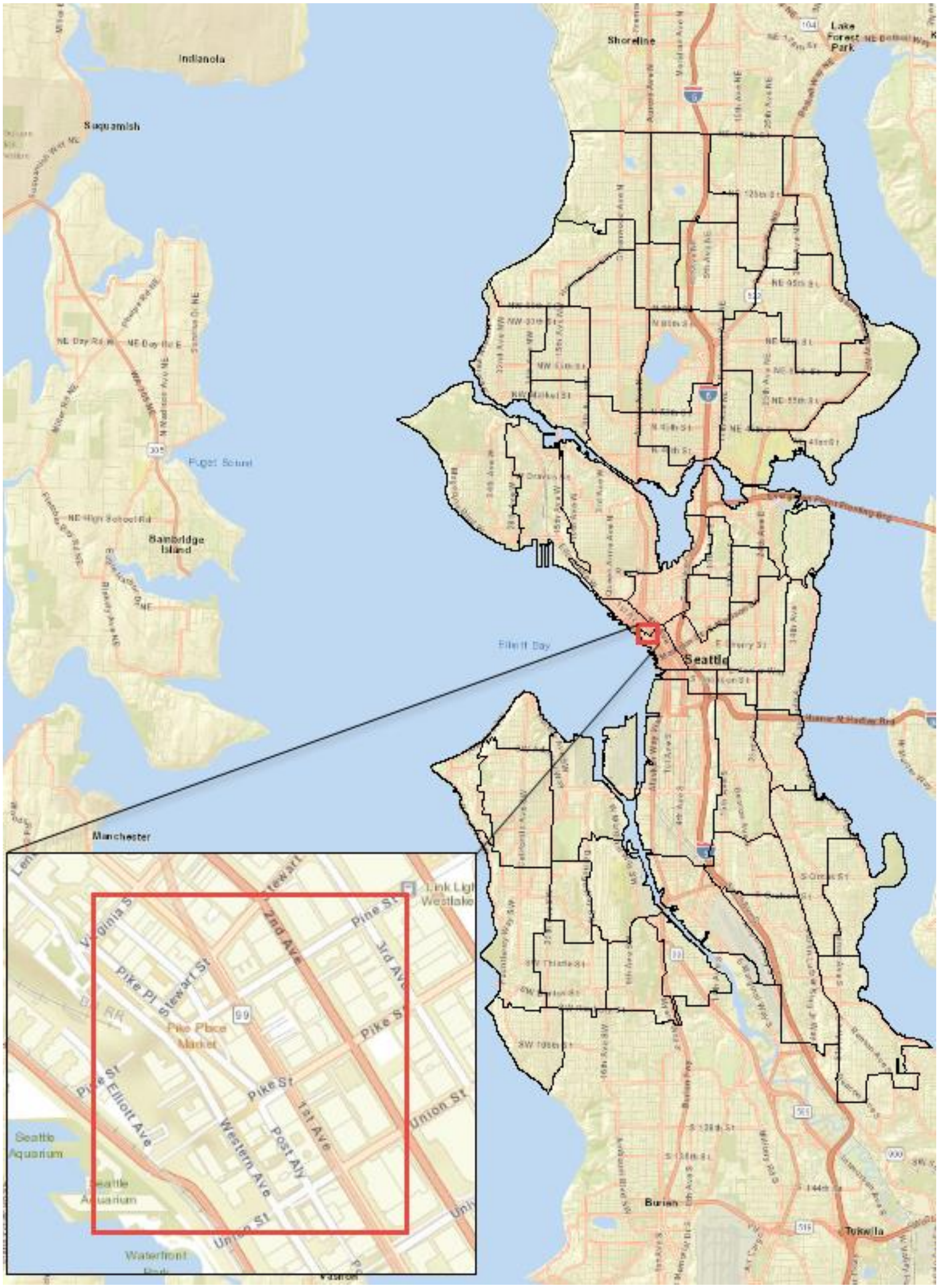

Figure 26e. Seattle, WA with focus area referenced.

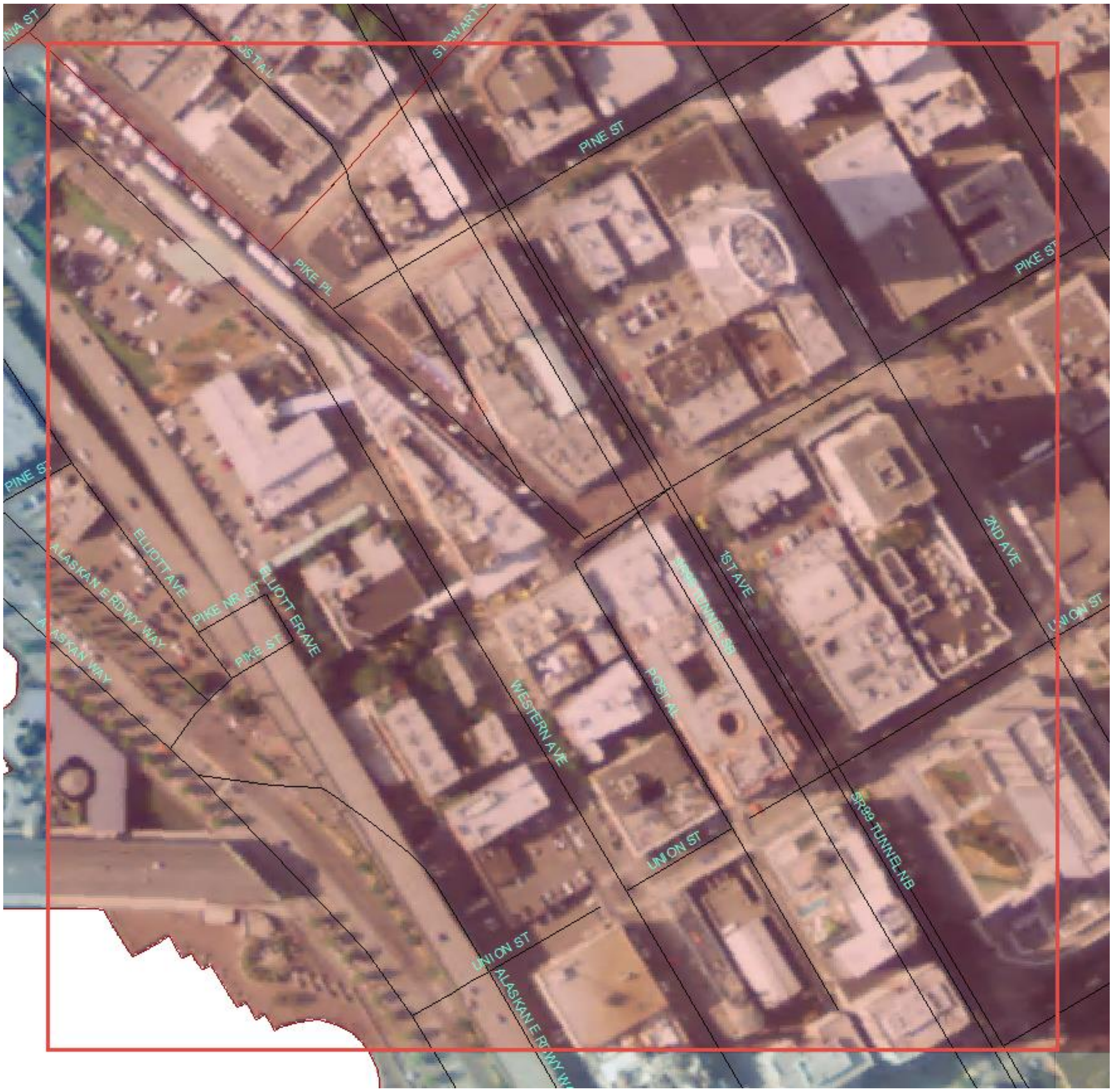

Figure 26f. Seattle focus area: Downtown Central Business District with Pike Place Market.

5.6.3 Chicago

Point density maps for Chicago showed that The Loop community, which is the central business district and the main part of Downtown Chicago (Figure 27a-d), was the area with a consistent high density of crime events.

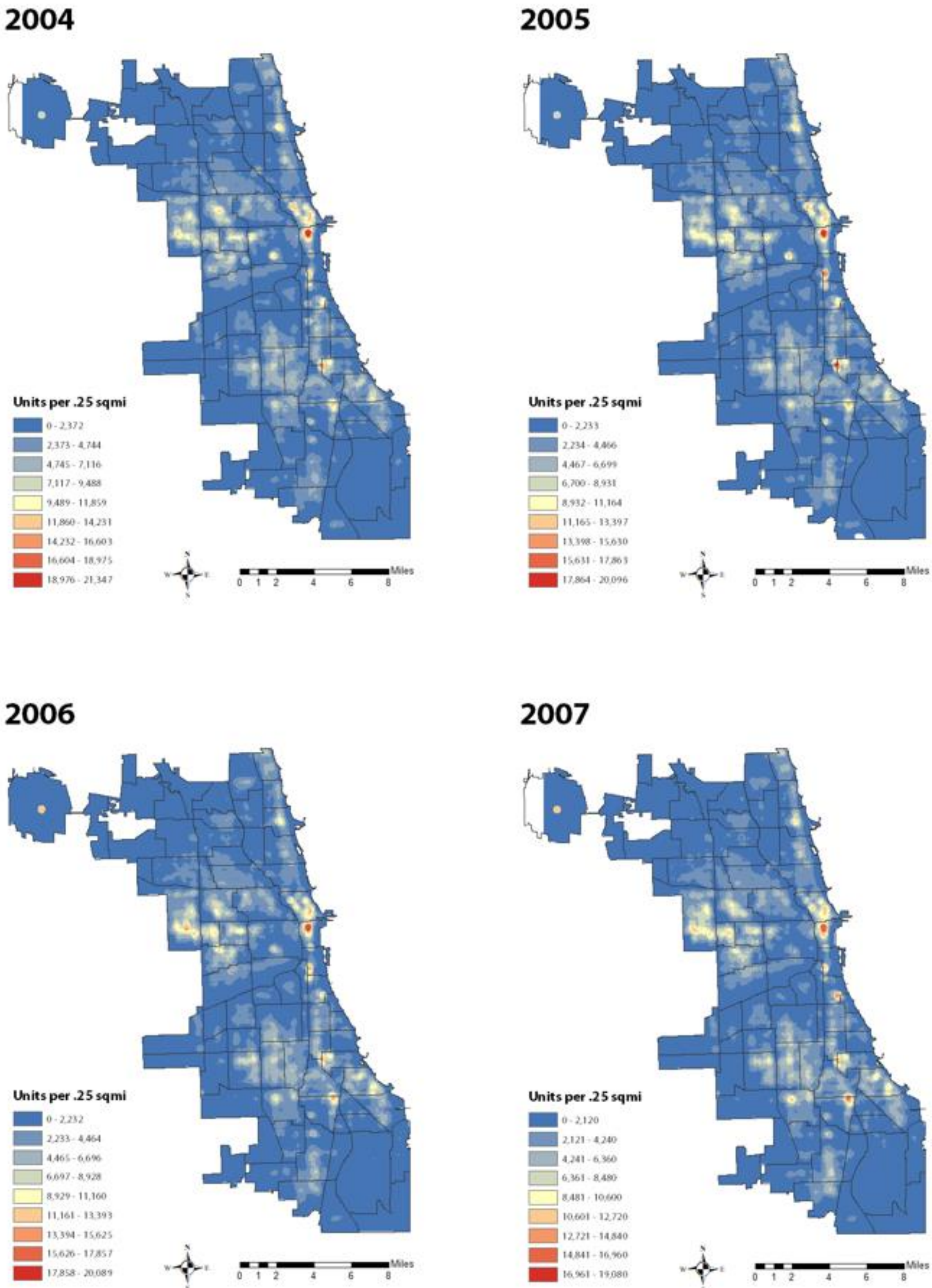

Figure 27a. Chicago point density maps showing concentration of crime, 2004-2007.

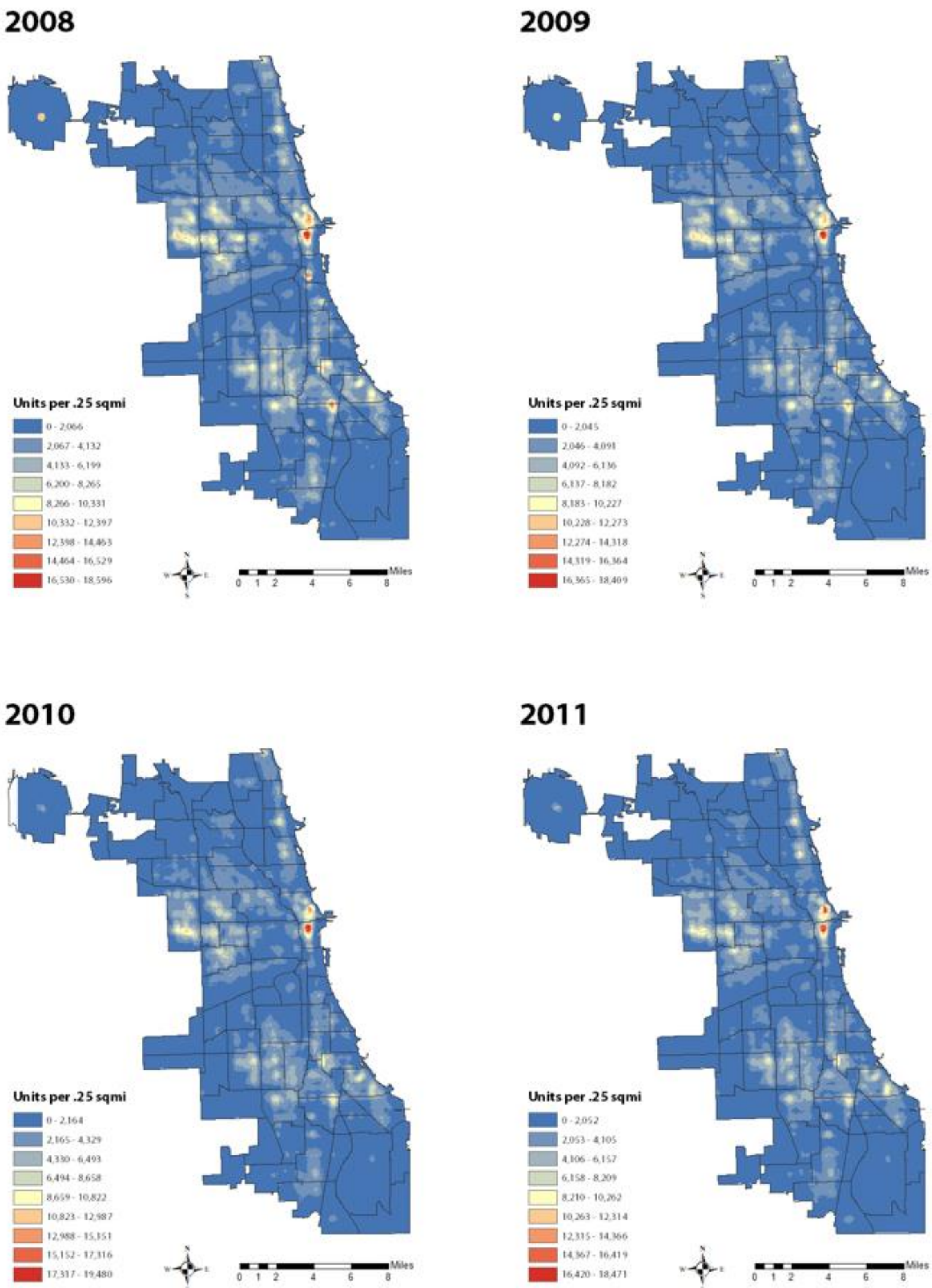

Figure 27b. Chicago point density maps showing concentration of crime, 2008-2011

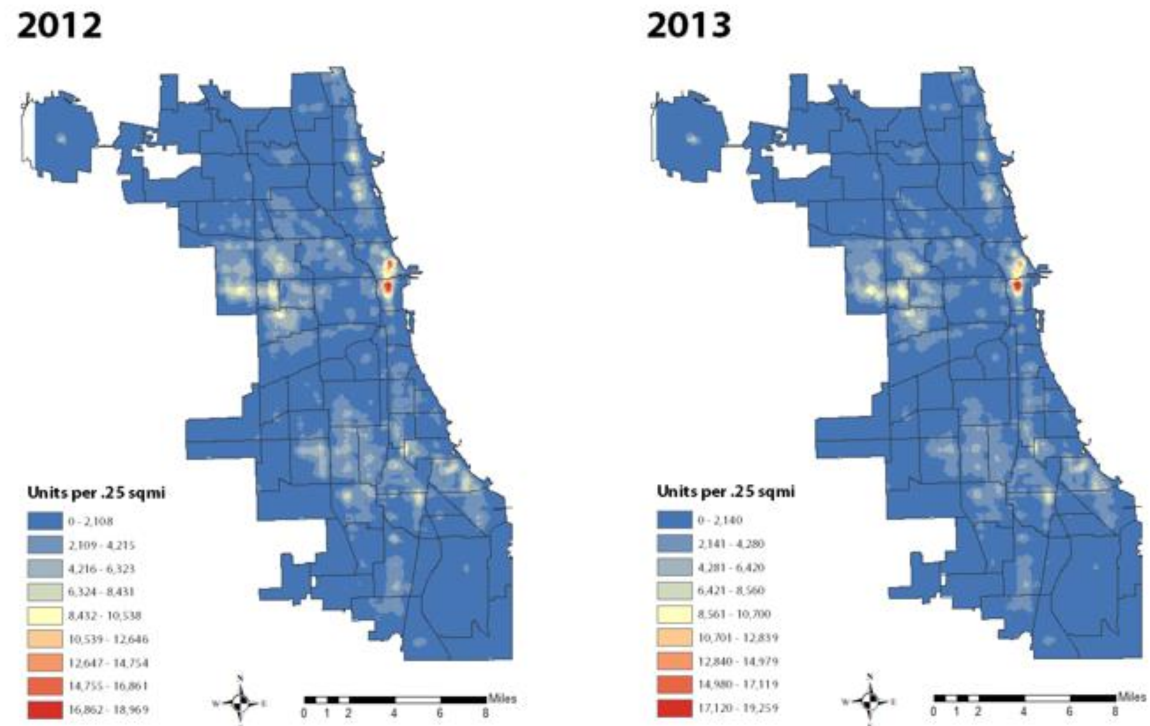

Figure 27c. Chicago point density showing concentration of crime, 2012-2013.

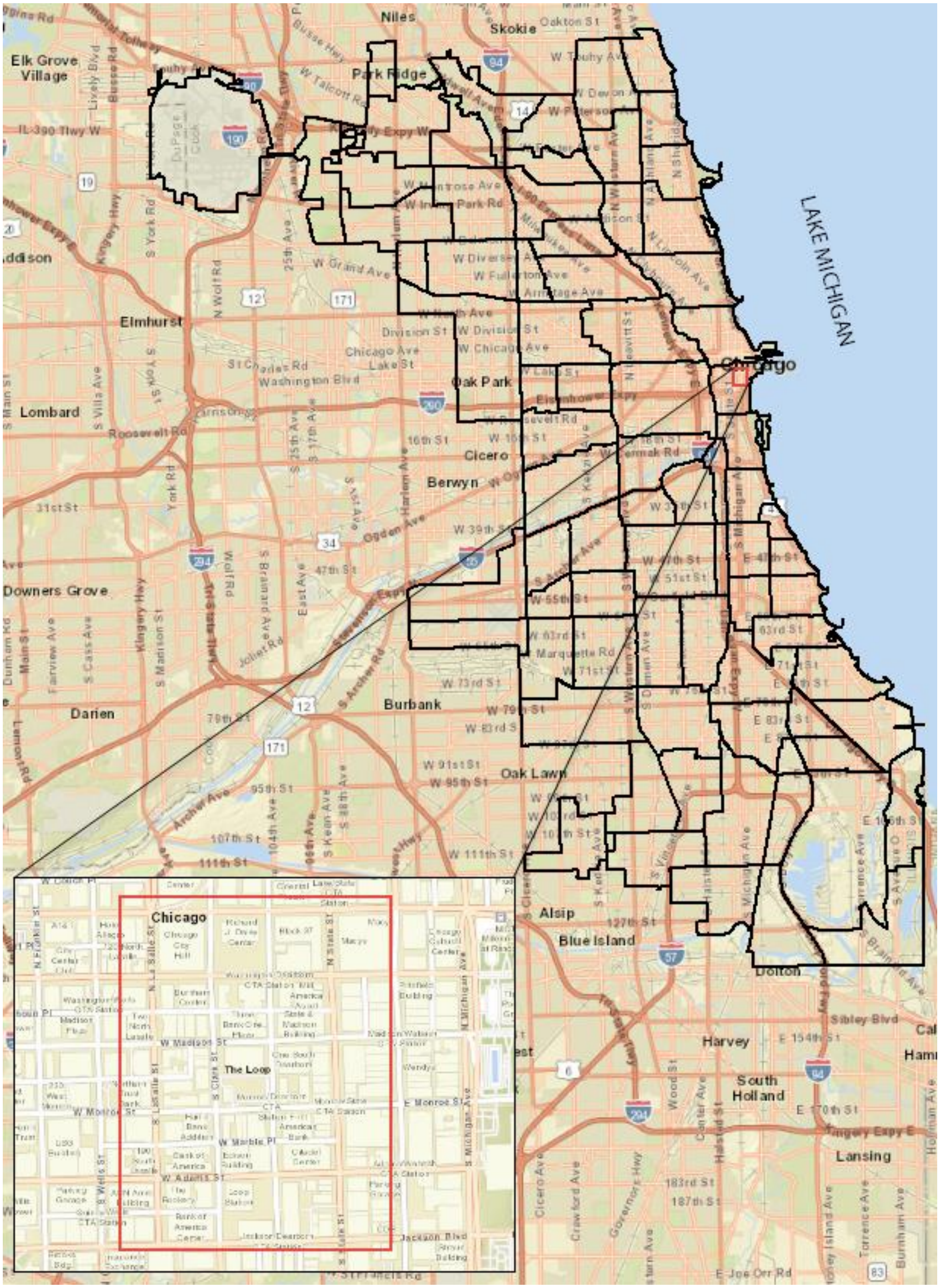

Figure 27d: Chicago reference map showing The Loop community identified by point density maps as the persistent high-density location.

However, the grid maps pointed to a different area (Figures 27e-g). From 2004 to 2010, there were many high frequency grids. The map for 2013 was the determining element, narrowing the candidate grids to just a handful. The selected focus area was at the intersection of three communities, Washington Park (approximately 12.5 percent), Greater Grand Crossing (approximately 12.5 percent), and Woodlawn (approximately 75 percent) (Figures 27h-i).

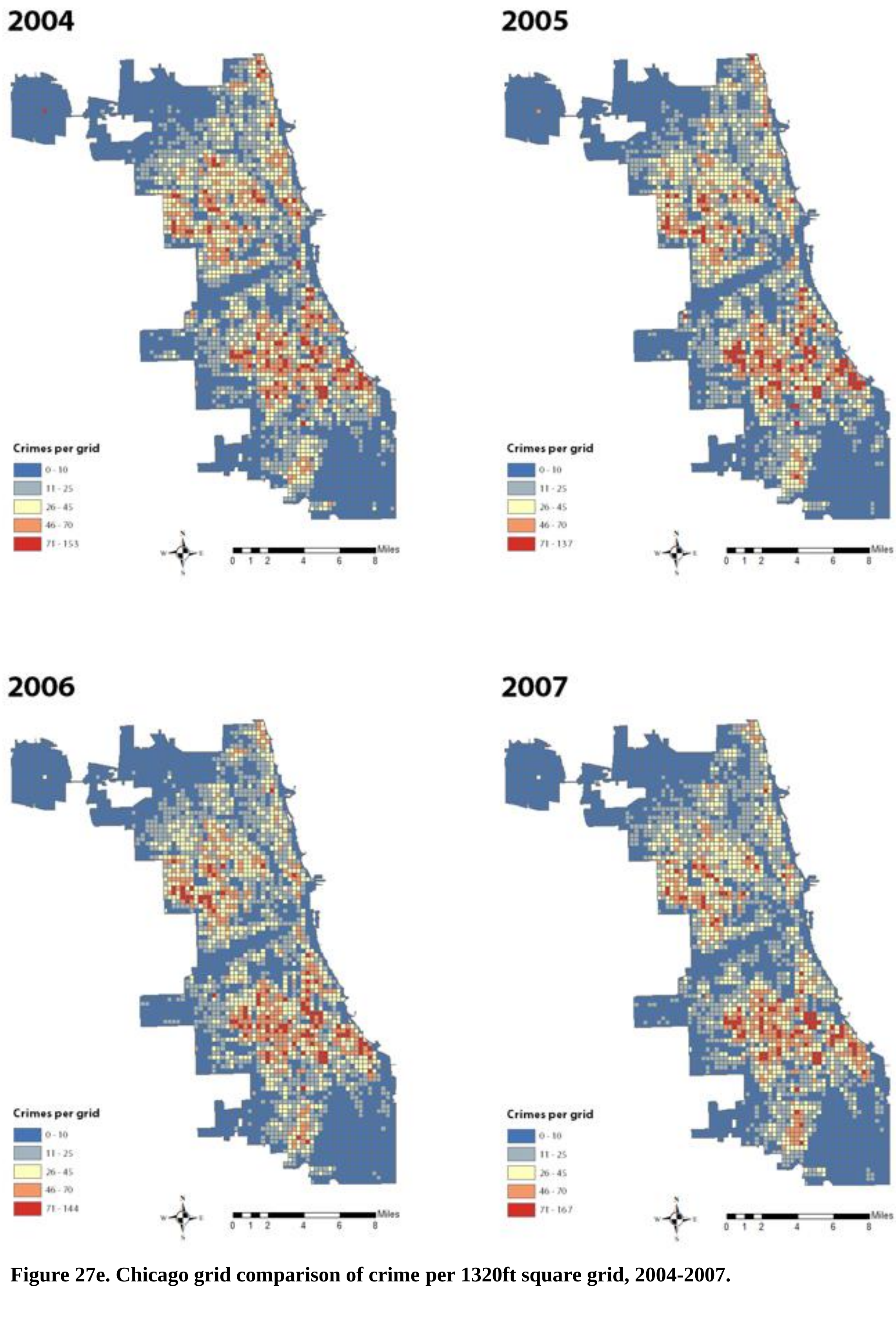

Figure 27e. Chicago grid comparison of crime per 1320ft square grid, 2004-2007.

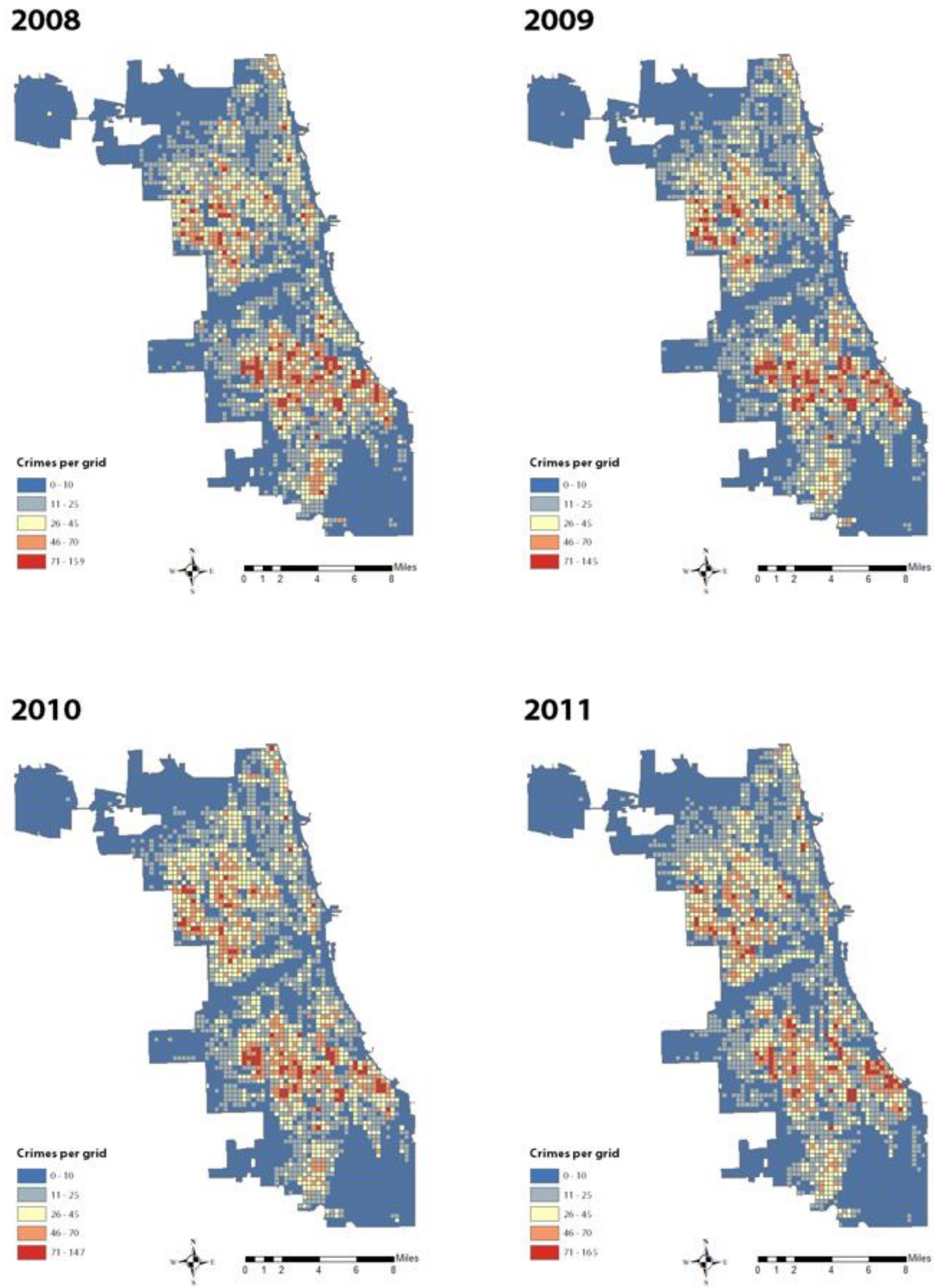

Figure 27f. Chicago grid comparison of crime per 1320ft square grid, 2008-2011.

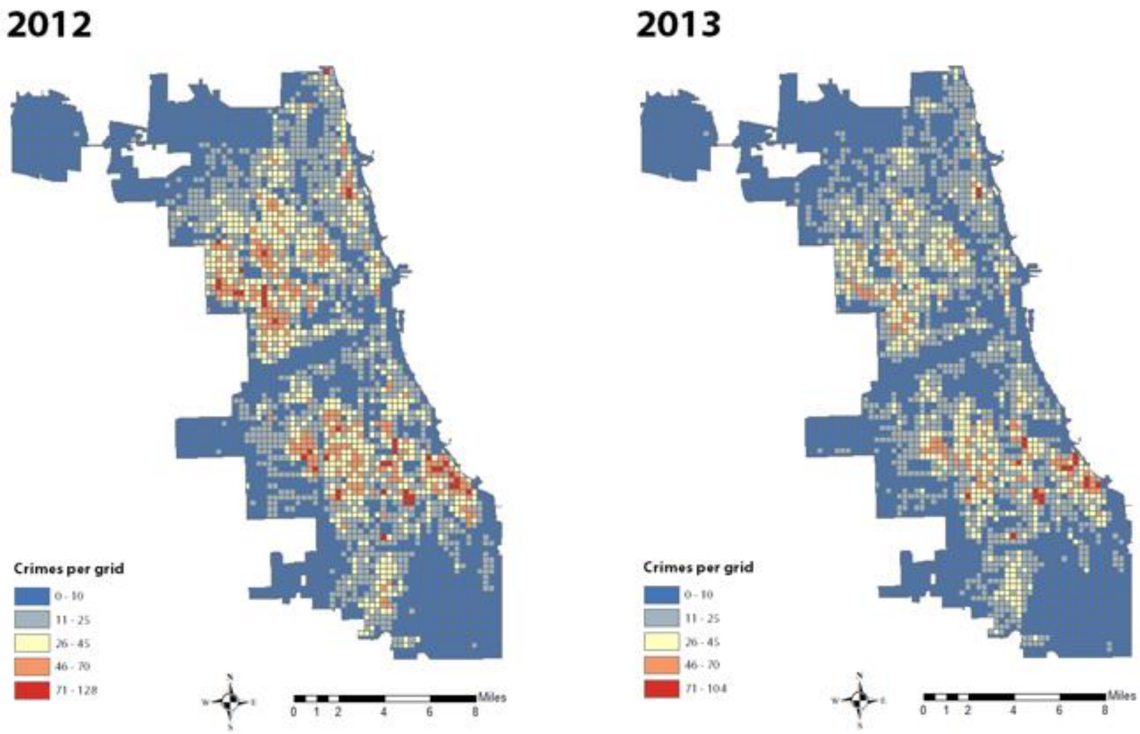

Figure 27g. Chicago grid comparison of crime per 1320ft square grid, 2012-2013.

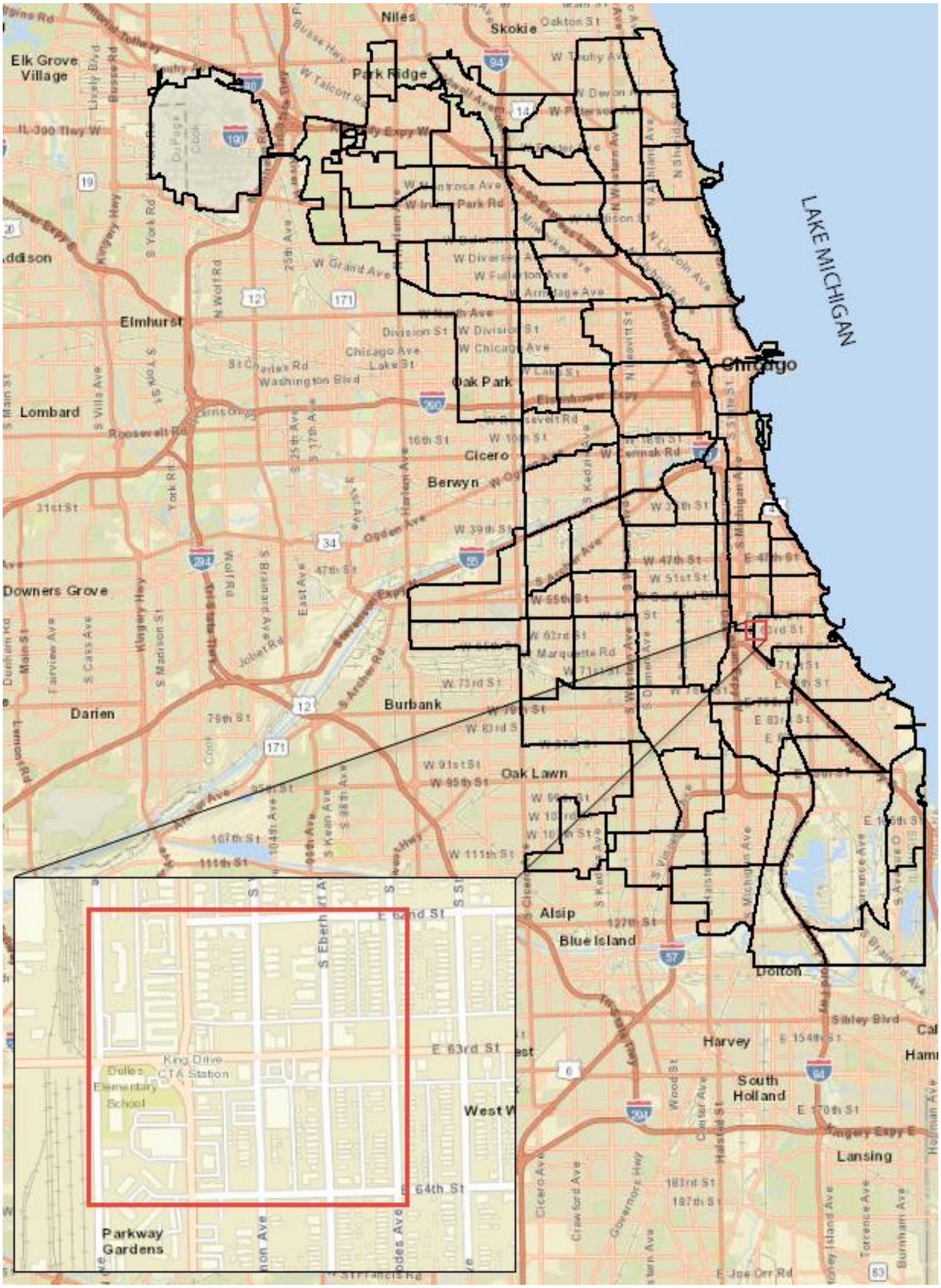

Figure 27h. Chicago, IL with focus area referenced in the Woodlawn, Greater Grand Crossing and Washington Park communities.

Figure 27i. Chicago focus area: Residential community areas of Woodlawn, Greater Grand Crossing and Washington Park

In Figure 27i, the Chicago Transit Authority (CTA) elevated ('L') train runs along 63rd Street with a stop at the intersection of 63rd Street and South Martin Luther King Drive. To the west of that intersection (or left in the image), is where Greater Grand

Crossing (lower left) and Washington Park (upper left) communities are located.

Woodlawn is east of South Martin Luther King Drive.

Chapter 6. Discussion

This research focused on the discovery of spatial and temporal relationships between violent and property crime, and the places in which those types of crimes were highly concentrated over a period of ten years for three regional cities in the United States. Using a longitudinal comparative analysis approach, the study sought to address the following questions:

1. *For the regional policing jurisdictions to be studied, what geographic factors are highly correlated with a change in reported crime and are these factors spatially and temporally similar for all three cities?*
2. *Which persistent clusters of crime cannot be explained by the factors revealed in Q1? For the identified locations, what types of mapping and visual analytic methods can be used to discover additional factors?*
3. *How can the factor-based methods used to answer Q2 be used to explain spatiotemporal patterns of crime both over time and across/within the three cities?*

The intent of this study was to show that, though hundreds or thousands of miles apart, crime patterns are very similar in attribute and temporal space. The results of analysis showed that there were both similarities and differences in the regional locations regarding attributes (factors) and times of how crime occurs from a longitudinal perspective. Additionally, some visual methods were more useful than others in discovering supplementary factors; however, the lack of identical data for all three locations made improved model development challenging.

6.1 Findings

To examine the overall distribution of crime in each city, Chapter 5.1 employed the use of thematic maps and box plots. The choropleth maps, which displayed rates for each neighborhood/community statistical area, identified neighborhoods with high and low rates of crime. Although the population was not the same for each city nor in each neighborhood area, calculating the crime rate at 1000 persons allowed for the use of similar breaks in the class boundaries across all three cities. The selection of the class breaks: 12.50, 25.00, 37.50 and 50.00, were influenced by the lower crime rates for Chicago. This meant that Atlanta, which had much higher rates overall, appeared to be suffering from extremely high rates of crime citywide compared to Chicago and Seattle, especially in the years 2008 and 2009. Atlanta had the smallest citywide population and Chicago had the largest (Table X).

Table 12. Census population for Atlanta, Chicago, and Seattle for 2000 and 2010 including the percentage of change

	Atlanta	Chicago	Seattle
2000	420325	2896016	563374
2010	420003	2695598	608660
% change	*-0.077*	*-6.920*	*8.038*

In lieu of that, I expected to find that Chicago had higher crime rates. That was not the case. Even in a direct graph comparison, Atlanta had the highest overall rates of crime and Chicago, at least for burglary and auto theft, had the lowest rates. (Figures X-X).

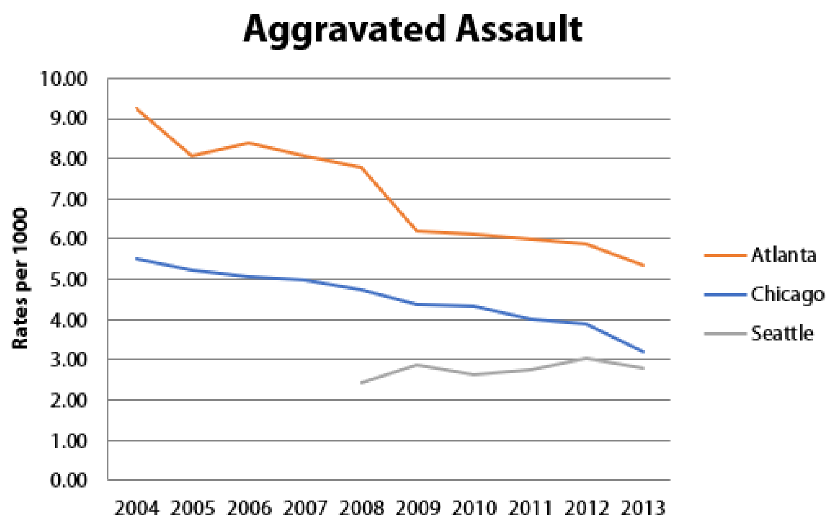

Figure 28a. Comparison of annual crime rates per 1000 persons for assault from 2004-2013.

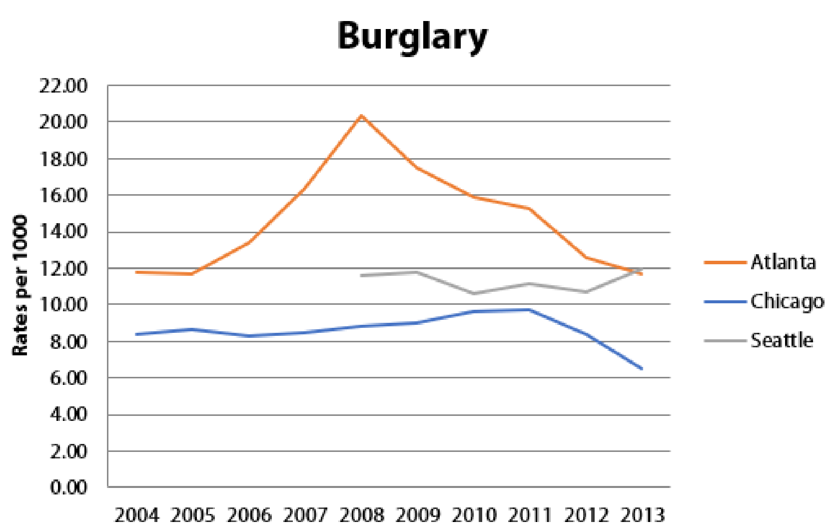

Figure 28b. Comparison of annual crime rates per 1000 persons for burglary from 2004-2013.

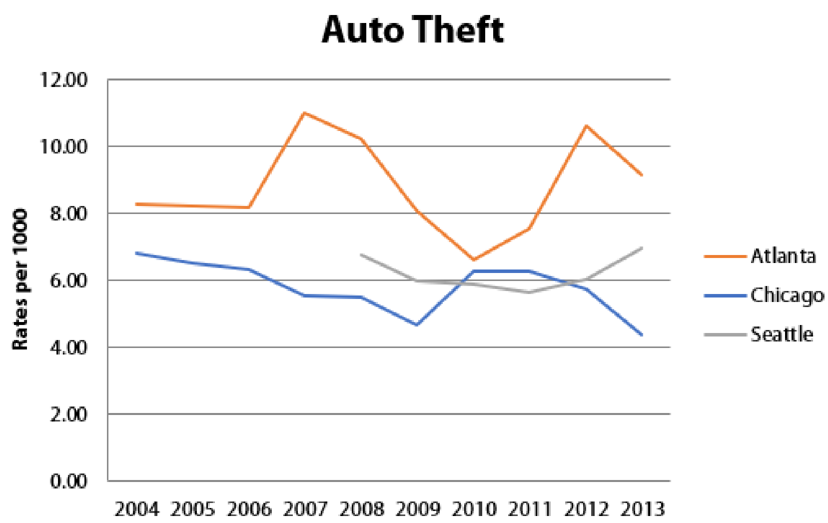

Figure 28c. Comparison of annual crime rates per 1000 persons for auto theft from 2004-2013.

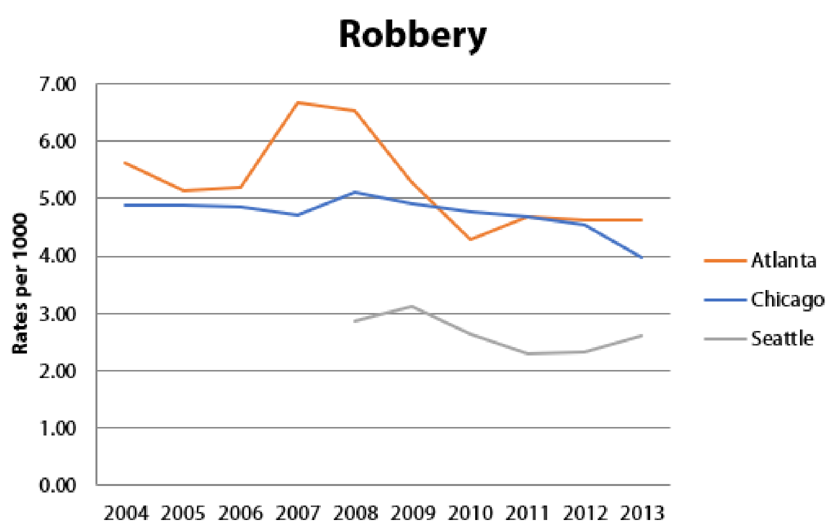

Figure 28d. Comparison of annual crime rates per 1000 persons for robbery from 2004-2013.

In Seattle, the four identified community statistical areas with the highest rates were also among the least populated community areas. After closer examination, it was discovered that these areas contain much of the downtown business, professional sports, entertainment and shopping attraction locations, to include Pike Place Market and Lumen Field (formally known as “The Clink” and home to National Football League’s Seattle Seahawks). Previous studies have found that such areas have higher daily and/or seasonal population which may contribute to the higher rates of crime by providing greater criminal opportunity with a reduced likelihood of detection (Brantingham and Brantingham 1995). Without a complete schedule of events for each of the study years, it cannot be stated for certain that higher daily and/or seasonal population directly influenced higher rates of crime. It can, however, be inferred that these attractions which increased the population both during the day and night, as well as during the week and on the weekends, was a direct influence on the higher incidents of reported crime, thus boosting the crime rate for those community areas.

It was also discovered that a higher median household income for a community area did not always mean lower rates of crime nor was it indicative of a lower density of crime. For example, in Chicago, The Loop was the community area with the second highest median household income for the city. Although it was in the mid-range regarding crime rates over the study years, the area identified with the point density maps as having the most persistent high-density crime was located within The Loop community.

In both Seattle and Atlanta, the identified high-density and high-frequency grid areas were the same, which was the central downtown business district. That was not the case with Chicago. As stated previously, The Loop was identified as the high-density area. That community represents Chicago’s central downtown business district. However, the identified grid area intersected the Washington Park, Woodlawn and Greater Grand Crossing communities further south in the city. In the crime rate maps, Washington Park was identified as having the most persistently high rate of crime, so there was similarity in that instance with the grid maps. On closer inspection of the aerial imagery for the selected tri-community area in Chicago, the Chicago Transit Authority (CTA) “L” train runs through the middle of the grid and divides the upper (Washington Park) and lower (Greater Grand Crossing) parts of the grid west of Dr. Martin Luther King Drive with a transit station at the of 63rd Street intersection. Parkway Garden Homes, a large privately-owned low-income apartment complex begins toward the bottom left corner of the grid. What is not seen, is the former location of a 16-story Chicago Housing Authority (CHA) apartment building called Randolph Towers, which was located in the upper left corner of the grid in the now grass area of Washington Park. The demolition of Randolph Towers at 6217 South Calumet Avenue was completed in the fiscal year of 2007 (CHA 2008). Randolph Towers provided a near-unchecked refuge for a high-profile, notorious gang called the Black Disciples. There were two other rival gangs operating in the area and their organized criminal activity had been attributed to much of the violent crime in the location in previous studies (Block 2000; Block and Block 1993; Papachristos 2009). The attribution of higher crime events to organized crime as a factor to include with a model was both unanticipated and improbable given the scope of this study and the varied methods of gang and organized crime activity collected by each city. The factor itself, however, cannot be completely dismissed.

In reflecting upon why an area within The Loop community was identified in the point density maps and not the grid maps, the answer may lie in the adjacency of attractions. The Loop, as stated earlier, is the central downtown business district for Chicago. The area contains theatre and arts venues, hotels, banks and restaurants. Adjacent to the area identified in the point density maps are two very large parks (one which has an amphitheater) and Soldier Field, home to the National Football League's Chicago Bears. These places are high-profile visitor attractors, therefore there would be hourly and daily fluctuations of population. As such, those attractors would also be generators of crime (Brantingham and Brantingham 1995).

Analysis with Atlanta data was more complex than with Seattle or Chicago. In the selected focus area, crime decreased from 2010 to 2011. The decrease was significant enough that it raised the question of what occurred to cause the decrease. It was discovered that in 2011, the Atlanta Police Department underwent a few administrative changes which may have impacted the occurrence of crime, the most significant change being the redrawing of police patrolling boundaries (Atlanta Police Department 2010). Whether that change alone was responsible for the decrease is unknown, as there was no publicly available data in reference to any applied policing strategies in the area. However, it could be inferred that the result of the change in the size of the policing boundary (which was divided into two sections, creating smaller patrol areas), was an increase in patrol officer visibility, thereby increasing the presumed risk for a potential offender. This would in turn reduce the occurrence of certain types of crime. Additionally, the change may have also temporarily pushed crime into bordering areas creating a decline in the statistics. Again, without information regarding applied crime prevention strategies, it cannot be stated definitively that the decline could be attributed to the policing boundary change.

6.1.1 Location Similarities and Differences

Policing styles for the three cities varied. Chicago and Atlanta police departments both used a Compstat method of policing. Seattle did not use a Compstat style of policing during the study years. It was not until 2014 that Seattle rolled out SeaStat, their form of

Compstat, to address crime hotspots within the city (SPD 2014; Geraghty et.al. 2016). Chicago changed how they used Compstat by reorganizing policing officers into patrol districts for better resources and accountability (BJA 2013). Whether the use of the Compstat method of policing had a lasting effect on the reduction of crime in Chicago or Atlanta remains unclear as there were other reasons surrounding crime reduction in several locations. Drastic reductions involved the removal of residents, then the subsequent demolition of public housing buildings and row housing. Of note, as mentioned earlier in this chapter, was the demolition of Randolph Towers in Chicago's Washington Park community. In Atlanta, through the Quality of Life Initiative and other demolition/revitalization initiatives, more than 10,000 public housing units were demolished across the city from 2003 to 2010 (AHA 2013).

"Metro Renters" was the common Tapestry Segment among all three cities and was also the top segment. Aside from that, the cities varied with regard to the predominate lifestyle and lifestage makeup of the neighborhoods (Appendix B). Because previous years of the Tapestry Segmentation data were not available, a comparison among the cities to determine if there were significant shifts in lifestyle and lifestage composition of neighborhoods was not completed.

Each city did not have an equal number of census blocks. Atlanta had 5,743 blocks, Seattle had 9,296 blocks, and Chicago had 47,064 census blocks. For the land area that Chicago covers (227 square miles), the city was quite dense with census blocks. Compared to Atlanta with 132 square miles and Seattle with 89 square miles (land only), there were at least five times the number of blocks. The delineation of blocks is not determined by population. According to the Census Bureau, blocks are delineated by using physical and administrative boundaries like streets, railroad lines, rivers, and streams. Thus, it is the design of the city itself that determined the number of blocks. As a comparison, New York City, which has 303 square miles of land, has 38,799 census blocks, and the City of Los Angeles, which covers 469 square miles, contains 30,691 census blocks.

There were a different number of administrative units for each city. Atlanta had 101 neighborhood statistical areas and 259 defined neighborhoods, Seattle had 53 community reporting areas and 91 named neighborhoods with 28 unnamed micro-neighborhoods, and Chicago had 77 named community statistical areas and between 98 and 200 unofficial neighborhoods. The city only recognizes the 77 community areas. Seattle and Chicago are port cities, whereas Atlanta is fully landlocked.

Based on the criteria mentioned in section 6.1, the area of focus for Atlanta and Seattle were in the downtown central business district. Additionally, those areas were proximity adjacent to areas of major tourism sites. For Seattle, that was Pike Place Market, which is located within the focus area, Miner's Landing at Pier 57, and the Seattle Aquarium. The focus area in Atlanta is in close proximity to Atlanta Underground – a major tourism attraction to the city. As previously discussed in the first part of this section, the focus area for Chicago was towards the south of the city. Adjacent to the location are the CTA and Norfolk Southern rail yards.

Because the focus areas for Atlanta and Seattle were business districts and contained or were adjacent to major tourist attractions, there was a presumption of a higher concentration of people in the locations throughout the year, which were not included in any statistical enumerations. This would make creating a viable predictive model difficult if using population as one of the model variables, even if daytime population estimates could be obtained, that would exclude night time population. For Chicago, a similar issue would exist, though the impact would be much less in comparison since the area is primarily residential. There is at least one major attraction during the summer in Jackson Park, which is a about three miles to the east.

6.1.2 Crime Similarities and Differences

At the city level, Seattle's violent crime rates were quite low compared to the property crime. This observation was similar for Chicago and Atlanta. As previously discussed in the beginning of this chapter, rates of crime looked very different from what I expected to see given the difference in population sizes of the cities. Atlanta consistently had higher rates of crime than Chicago and Seattle. And only with violent crime were Seattle's rates lower than Chicago. Neighborhood level analysis revealed high-density locations in the downtown neighborhoods for all three cities.

Within the focus areas, robbery and burglary were the most frequently reported incidents for Seattle. For Atlanta and Chicago, the most frequently reported incidents were robbery and aggravated assaults. The fewer burglaries may be due to fewer residential dwellings located within the area itself in Atlanta, as the majority of the location is federal, state and local government. Chicago and Seattle obfuscated their data to the block address. At the time of collection, Atlanta's crime data was exact address.

6.1.3 Attribute Similarities and Differences

Each city had different consistent attributes across all four crime types at the neighborhood level. Chicago had two (vacant housing and places of worship), Seattle had six (total population, median household income, owner occupied housing, transit stops, places of worship, and police stations) and Atlanta had one (transit stops) (Tables 3-5). This may be due to the different sizes of neighborhoods, as they were the pre-defined local administrative boundaries in each location.

Attribute similarities for Aggravated Assault (Tables 13a-13c) for all three cities were Median household income, Shelters, and places of Worship. Atlanta and Seattle shared Transit stops, while Seattle and Chicago shared Total population.

Table 13a. Assault attribute comparisons between cities (*italic* = positive relationship)

Assault	Atlanta	Chicago	Seattle
	median household income	*total population*	total population
	renter occupied housing	median household income	median household income
	bars	occupied housing	*transit stops*
	transit stops	*vacant housing*	*shelters*
	shelters	*shelters*	*check cashing facilities*
	places of worship	*places of worship*	*places of worship*
		rehabilitation facilities	*clubs*
			police stations

Table 13b. Assault attribute differences between cities (*italic* = positive relationship)

Assault	Atlanta	Chicago	Seattle
	renter occupied housing	*total population*	total population
	bars	occupied housing	*transit stops*
	transit stops	*vacant housing*	*check cashing facilities*
		rehabilitation facilities	*clubs*
			police stations

Table 13c. Assault attribute similarities between cities (*italic* = positive relationship)

Assault	Atlanta	Chicago	Seattle
	median household income	median household income	median household income
	shelters	*shelters*	*shelters*
	places of worship	*places of worship*	*places of worship*

For Robbery (Tables 13d-f), all three cities had Renter occupied housing and Shelters in common. Chicago and Seattle were similar with Median household income and Check cashing facilities. Atlanta and Seattle were similar with Transit stops.

Table 13d. Robbery attribute comparisons between cities (*italic* = positive relationship)

Robbery	Atlanta	Chicago	Seattle
	occupied housing	median household income	median household income
	renter occupied housing	*vacant housing*	renter occupied housing
	transit stops	*renter occupied housing*	*hospitals*
	shelters	*shelters*	*transit stops*
	liquor stores	*check cashing facilities*	*shelters*
		police stations	*check cashing facilities*
		rehabilitation facilities	*places of worship*
			clubs
			malls

Table 13e. Robbery attribute differences between cities (*italic* = positive relationship)

Robbery	Atlanta	Chicago	Seattle
	occupied housing	median household income	median household income
	transit stops	*vacant housing*	*hospitals*
	liquor stores	*check cashing facilities*	*transit stops*
		police stations	*check cashing facilities*
		rehabilitation facilities	*places of worship*
			clubs
			malls

Table 13f. Robbery attribute similarities between cities (*italic* = positive relationship)

Robbery	Atlanta	Chicago	Seattle
	renter occcupied housing	*renter occupied housing*	renter occupied housing
	shelters	*shelters*	*shelters*

Vacant housing and Transit stops were similar attributes for all three cities with Burglary (Tables 13g-i). Seattle and Atlanta shared Median household income, whereas Atlanta and Chicago shared Rehabilitation facilities.

Table 13g. Burglary attribute comparisons between cities (*italic* = positive relationship)

Burglary	Atlanta	Chicago	Seattle
	median household income	*vacant housing*	*total poulation*
	vacant housing	*transit stops*	median household income
	atms	clubs	*vacant housing*
	transit stops	rehabilitation facilities	*transit stops*
	check cashing facilities		shelters
	liquor stores		*places of worship*
	rehabilitation facilities		

Table 13h. Burglary attribute differences between cities (*italic* = positive relationship)

Burglary	Atlanta	Chicago	Seattle
	median household income	clubs	*total poulation*
	atms	rehabilitation facilities	median household income
	check cashing facilities		shelters
	liquor stores		*places of worship*
	rehabilitation facilities		

Table 13i. Burglary attribute similarities between cities (*italic* = positive relationship)

Burglary	Atlanta	Chicago	Seattle
	vacant housing	*vacant housing*	*vacant housing*
	transit stops	*transit stops*	*transit stops*

The single common attribute for Auto Theft (Tables 13j-l) was Median household income. Atlanta and Seattle had Transit stops in common. Chicago and Seattle were similar with Total population, Rehabilitation facilities, Bars, and Shelters.

Table 13j. Auto Theft attribute comparisons between cities (*italic* = positive relationship)

Auto Theft	Atlanta	Chicago	Seattle
	median household income	*total population*	*total population*
	occupied housing	median household income	median household income
	schools	*vacant housing*	*bars*
	transit stops	bars	atms
	check cashing facilities	*shelters*	*transit stops*
	malls	rehabilitation facilities	shelters
			rehabilitation facilities

Table 13k. Auto Theft attribute differences between cities (*italic* = positive relationship)

Auto Theft	Atlanta	Chicago	Seattle
	occupied housing	*total population*	*total population*
	schools	*vacant housing*	*bars*
	transit stops	bars	atms
	check cashing facilities	*shelters*	*transit stops*
	malls	rehabilitation facilities	shelters
			rehabilitation facilities

Table 13l. Auto Theft attribute similarities between cities (*italic* = positive relationship)

Auto Theft	Atlanta	Chicago	Seattle
	median household income	median household income	median household income

Atlanta was the only city that had Malls as an attribute for auto theft, and when examining the patterns, a higher concentration of incidents did in fact occur in and around shopping center parking lots and structures. While this also occurred with Seattle, the factor did not have a strong enough correlation to be included in the initial specified model.

For all three cities, places of worship were highly positively correlated with the crime types, especially for Aggravated Assault. This was unexpected and remains largely unexplained from the perspective of non-rural communities. While there is limited research exploring the relationship between churches and neighborhood crime, those studies lean more towards the "individual level effects that religious beliefs or religious affiliation have on criminal behavior" (Willits, Broidy, Gonzales and Denman 2011) in rural communities. Of the few studies that focused on broader effects of churches on crime, researchers examined the phenomenon from the theoretical perspectives of social disorganization and routine activity. Of note was a theory that since churches bring people together, there would exist the notion of informal social control. In other words, the congregation would informally engage in a type of "self-policing", acting as a pseudo deterrent to individuals' intent on committing crime (Cohen and Felson 1979). Without a larger body of empirical research, I can only speculate that the positive correlation between places of worship and crime for this study has more to do with the concentration of the establishments within neighborhoods, which brings more people into a location at a particular time of day. Moreover, it is commonly known that some places of worship also function as shelters and/or soup kitchens as part of their service to a community, which may result in an unintentional attraction of criminal behavior by outside actors targeting those in need whom would visit the location to take advantage of the services provided.

Rates of unemployment were different for each city. Data collected from the United States Bureau of Labor Statistics showed that non-seasonally adjusted rates for all three cities increased significantly during the economic downturn which began its nationwide impact in mid-2008 (Figure 29).

Figure 29. Unemployment rates comparison 2004-2013

Seattle appeared to recover much more quickly than the other two cities. Both Chicago and Atlanta maintained rates at approximately 4 to 5 percent above pre-recession rates. In examining the trend, as unemployment rates increased, crime (in general) decreased. Unfortunately, unemployment data at the neighborhood statistical level was inconsistent for each city, therefore attempting to add unemployment as a model factor was not feasible. Chicago had employment data by community area for the 2000 decennial census enumeration, but not for each year. Atlanta had unemployment data estimates for each neighborhood statistical area, however, it was from the American Community Survey 2008-2012 profile years. Seattle had no employment data broken down by community.

6.1.4 Temporal Similarities and Differences

Deciding on an appropriate temporal scale for imagery and other non-crime data that matches with temporal aspects of the census data was a challenge. Captured imagery from Google Earth Pro was inconsistent for the years covering the study. There were images blocked by low cloud cover and the imagery were generated from different providers, like Landsat, and the US Department of Agriculture.

Using calendar dates as the temporal component, for all locations, the warmer months of May, June, July and August contained the higher counts of violent crime events citywide. There was also a general decrease across all crime types beginning in 2008. In Chicago, the Halloween holiday, regardless of the day of the week it fell, had unusually high numbers of reported assaults.

The time of day for reported crimes was similar for all three cities, strictly speaking, in two crime types. Assaults were highly reported as occurring between the hours of 1800 and 0000 as was robbery. For burglary and auto theft, the most frequently reported times were 0601-1200 for Atlanta and Chicago. Seattle's time was 1201-1800 for burglary and 0601-1200 for auto theft.

The day of the week was most similar for aggravated assault. The weekend was the most frequently reported day. Weekdays were reported more frequently for burglary. For robbery, Chicago and Atlanta had Friday as the higher reported day, while Seattle had Sunday. And for auto theft, Saturday, Monday and Friday were the most reported days for Atlanta, Seattle and Chicago, respectively.

6.1.5 Regional Model Performance

A base model was developed using six similar factors. The factors were Median household income, Shelters, places of Worship, Renter occupied housing, Vacant housing, and Transit Stops. These six attributes were shared among the three cities across the four crime types. I believed the model to be weak, as it only included six factors. I did not expect the model to improve upon any of the previous results as the factors I anticipated for inclusion in a regional model either had no strong correlation or could not be added due to inconsistencies with data availability in each city. However, with Chicago, the regional model improved the GWR results for all crime types.

In reviewing the Adjusted R-squared values using the regional model for Chicago compared to the individual specified models, assault performed about 1 percent better. Burglary had 5.4 percent increase. Auto theft increased by 8.4 percent and robbery had the greatest increase of just over 12 percent. There was some clustering of residuals for auto theft, however, the overall results were impressive.

In contrast, the regional model in Atlanta produced a very slight improvement over the specified model for assault. For the other crime types, the regional model performed worse than the specified model for each crime type, and for burglary it was just over a 10 percent reduction in the Adjusted R-squared value. For Seattle, the regional model produced even worse results. In fact, when testing the model with auto theft, its performance was 14 percent lower than the specified model. The exception in Seattle was burglary, which saw about a 3 percent improvement over the specified model for that crime type.

6.2 Challenges and Limitations

As discussed in the previous section, this study was not without its challenges and limitations. Ideally, the use of computational methods to address the questions posed were expected to be straightforward. Unfortunately, they were not due to several circumstances, the most impactful was the unavailability of identical data from all three cities covering the study period. This hindered the ability to identify additional factors to incorporate into the regional model.

Additionally, using decennial census data as a factor does not account for the dynamic fluctuations of social factors, meaning the increase and decrease of population, median household income, median age, and housing tenure each year. While American Community Survey (ACS) data could be used to fill in the gaps, the 5-year estimates would have been the best option producing the smallest sampling error (NRC 2007). That would have still meant missing demographic data changes that may have had an impact on the variability of crime rates.

A similar limitation existed for the geographic factors used for this study. Without business and land use data for each year, data collected represented a snapshot in time. Furthermore, for Chicago and Atlanta, drastic changes in the landscape during the study years, may have affected analysis results. These changes included public housing demolition, development in both the downtown and suburban areas, economic commerce closures due to the recession, and major revitalization activities.

6.3 Implications and Suggestions for Future Research

Despite the unexpected challenges and unexpected results, the study did produce an important and significant finding: obtaining identical data from multiple cities for an inter-regional comparative, longitudinal research was a considerable challenge. Studies in the field of comparative analysis have outlined similar difficulties in harmonizing data, including data quality, diversity, and the lack of existing identical data for multisite research analysis (Keim, et. al. 2008; Schröttle and Meshkova 2018;). Though the referenced studies were cross-national, meaning the comparative analysis of two or more countries, the complications with harmonizing collected data were analogous. Data reporting, collection, maintenance, and availability were not the same for my three study areas.

With additional independent variables, like unemployment rates, event data, climate data, building/construction projects and population changes at the neighborhood level, a model may be able to be developed such that it provides a level of predictability for an area regardless of its regional location. Furthermore, if reliable data like the existence of criminal enterprise (i.e., gangs or organized crime syndicates) within a community could be acquired for each of the study years, it may strengthen the model results or redefine model attribute correlations. This is in light of the results from Chicago where much of the crime in the selected area may be attributable to the presence of high-profile, rival gangs. It is worth furthering the research if such micro-scale data can be obtained across the years being analyzed.

Perhaps incorporating the use of a gravity model (Haynes and Fotheringham 1984), which uses both scale and distance impacts, to explore the generation and attraction of crime events would be useful in helping to identify unknown or hidden attributes. Building a strong model to discover potentially hidden crime attractors in persistent high-density clustered areas will require the collection of a great deal of diverse data.

It may be possible to go beyond simply identifying clustered locations using traditional techniques to analyze crime. By incorporating self-organizing maps to explore the notion of attribute space, such analyses may be able to reveal hidden relationships of which may not necessarily lend themselves to geographic space (Skupin and Agarwal 2008). Additionally, those hidden relationship patterns may produce a different perspective on how crime events cluster over time.

Another methodological approach to this study may be the use of small-area spatial statistics. It is mostly used in epidemiology and other health-related disciplines; however, given that the individual locations are about the size of a metropolitan census block, the analysis may benefit from kriging with small area estimation or the use of Bayesian hierarchical spatial models using integrated nested Laplace approximations (DiMaggio 2015). In the latter, the author explored the risk of pedestrian and bicyclist injuries due to traffic collisions over a 10-year period. Whether such method approaches will help alleviate the issues encountered with this study remains to be seen.

Moreover, should research be continued under the parameters of this study, it may be best to work with a single regional location at a time, as data collection can be tailored to that specific area. Resources for finding diverse data may be more robust, thereby possibly creating a better scenario for reproducing this study on a smaller, more manageable scale. Furthermore, after completing the studies in the single locations, a more appropriate set of cross-regional predictors may be identified to produce an advanced, better-performing model for longitudinal analysis of high-concentrations of crime.

Chapter 7. Conclusion

The objective of this study was to examine the spatial and temporal relationships between violent and property crime and the places in which these crimes occurred by analyzing a collection of factors to determine their influence – whether attracting or generating crime – in selected high-density locations. The resulting model was to help explain the existence of long-term spatiotemporal patterns in three regional cities across the United States. While the goal of developing a multi-dimension spatial and temporal model was not met, there were a few significant findings, which may be useful for researchers conducting a similar study. The following is a summary of the study with regard to the questions posed.

7.1 Question 1

To address the first question, "*What geographic factors are highly correlated with reported crime and are these factors spatially and temporally similar each year?*", I used exploratory regression, OLS and GWR to identify factors unique to each city and factors that were similar in all three locations. I also used calendar heatmaps, charts and graphs to ascertain similarities in the temporal aspects of the reported crime for each city. Spatially, Atlanta and Seattle were more alike and temporally, Chicago and Atlanta were more similar. There were similarities shared amongst all three cities which included six demographic and geographic factors, and two temporal similarities regarding the time of day for reported incidents of crime.

The process required gathering crime data, census data (to include population, income and housing occupancy status), and other data to include locations of hospitals, malls, ATMs and liquor stores – essentially starting with variables that seemed to be obvious. The collection of "snapshot" data (from a specific period of time) and applying the data to analyses across multiple years assumed there would be no change in the dataset itself. This was (and is) unrealistic, and yet was the best approach to determining what variables to use for an initial exploratory analysis. While it may have been possible to use a method like the spatial scan statistic (Kulldorf 1997) to calculate landscape changes over time, such a method would not have been plausible given the nature of the point data and its collection time – which was well after the years much of the physical data points, like the installation of an ATM, would have been created. Essentially, because an ATM is currently in the location does not mean that it was there two years prior or even five years prior.

Some data like unemployment rates and building/construction projects at the neighborhood level for all the years covered in the analysis and for each city was unattainable. Each location had partial data, but not for the entire period and some data could not be collected for the study period – though it was available for more recent years. Such was the case with the crime data (Seattle). However, Seattle did have crime data available from 2008 forward, and it was determined that six years was sufficient to include the city in the study.

7.2 Question 2

To respond to the second question, "*Which locations of persistent high-density crime cannot be explained by the factors revealed in Q1; and what types of mapping and visual analytic methods can be used to discover additional factors?*", an assessment of the specified models for each crime type was conducted, then a comparison was made between each city. After finding similar factors from each city, a regional model was created and tested. For Atlanta and Seattle, 20 percent of the crime could not be explained by the factors in the regional model. For Chicago, it was 12 percent. Historical aerial and street imagery were used to locate addition factors to include in the regional model. However, the locations were different, thus, the factors discovered for Chicago would not have necessarily applied to Atlanta and Seattle.

While some high crime activity on national holiday events and celebrations like July 4 and October 31 were revealed in a temporal visualization – in Chicago specifically, other events like National League Baseball/Football/Hockey games or city marathons were much less obvious and would have required gathering sports data, convention data, and entertainment data, et cetera for each year to determine their significance. Such data collection for the three cities was challenging as the data was vast and inconsistently maintained, meaning finding identical data for all three cities and confirming that the data were complete (within reason) was implausible given the time constraints for the research and the lack of reliable data in each location.

As noted in Chapter 5.5, only one city (Atlanta) had a more diverse, publicly available dataset that included land use and construction permitting covering the period of analysis. Similar data for the other two cities did not date further back than 2016. For reproducibility purposes, it was important for all the data used in this study to be available to the public.

7.3 Question 3

Lastly, the third question, "*How can the factor-based methods used to answer Q2 be used to explain spatiotemporal patterns of crimes both over time and across/within the three cities?*" could not be appropriately answered. Though it was possible to create a base regional model, that alone was not sufficient to explain the patterns revealed beyond what has already been discovered in previous studies in the geography and criminology domains. The temporal component of a properly specified regional model was a necessary element. A work-around may have been to further isolate specific street segments within the target location and calculate the moving average. Doing so, however, may not have produced a method that could be applied in all three locations.

While the study did not produce markedly novel insights, the research did expose a few things. First, it is not, generally speaking, the case that increased population equals higher concentrations of crime, especially when examining crime over an extended period of time – beyond two or three years. As shown in the case of Chicago, one of the consistently highest concentrations of crime was in an area with an overall lower population and not much in the way of high-profile attractions as what would be found in a downtown neighborhood. And second, obtaining consistent, identical data for multiple jurisdictions, let alone a single jurisdiction, is an issue which may not have an immediate solution. Spatial data (particularly GIS data), social and economic data, planning data, and even crime data are not created, collected nor maintained in an equitable and uniform manner across the United States. Discovering a method to perform meaningful, micro-level analysis using non-identical data for the moment remains a challenge.

The patterns and correlated factors/predictors discovered in this study may not be ground-breaking, however, I believe this research provides a base to expand upon. Moreover, I believe that with the development of an improved model stemming from Q2, the design of a regional model that could also be applied for micro-level analysis is possible.

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Appendix A

```
## ---------------------------------------------------------------------- ##
## Atlanta Crime Data
## ---------------------------------------------------------------------- ##
#### Libraries
## Load libraries
library(readr)
library(plyr)
suppressPackageStartupMessages(library(dplyr))
suppressPackageStartupMessages(library(lubridate))
library(ggplot2)
library(hms)
library(forcats)
library(extrafont)
library(extrafontdb)
library(writexl)
library(tidyverse)
library(readxl)
library(ggpubr)
library(xlsx)

#### Import data
## Set working directory
setwd("P:/.../crimeData/atl")

## Load in each file
```

```
crimes04 <- read_excel("atl_offenses/excel_files/2004/crimes04.xlsx")

crimes05 <- read_excel("atl_offenses/excel_files/2005/crimes05.xlsx")

crimes06 <- read_excel("atl_offenses/excel_files/2006/crimes06.xlsx")

crimes07 <- read_excel("atl_offenses/excel_files/2007/crimes07.xlsx")

crimes08 <- read_excel("atl_offenses/excel_files/2008/crimes08.xlsx")

crimes09 <- read_excel("atl_offenses/excel_files/2009/crimes09.xlsx")

crimes10 <- read_excel("atl_offenses/excel_files/2010/crimes10.xlsx")

crimes11 <- read_excel("atl_offenses/excel_files/2011/crimes11.xlsx")

crimes12 <- read_excel("atl_offenses/excel_files/2012/crimes12.xlsx")

crimes13 <- read_excel("atl_offenses/excel_files/2013/crimes13.xlsx")


# Remove the last three columns. They are duplicate columns and will not be used.

# (2004 - 2009)


crimes04 <- crimes04 %>%

    select(-c(30, 31, 32))


# Rename column to get rid of the # in the name (this is for 2004 - 2010)

colnames(crimes04)[colnames(crimes04) == "UCR#"] <- "UCR"

colnames(crimes04)[colnames(crimes04) == "INCIDENT#"] <- "INCIDENT_NUM"


# Find the NAs in the data - basically to make sure they are not in the columns you need

# for analysis - do this for all 10 years.


map(crimes04, ~sum(is.na(.)))
```

```
# Change TM_FM and TM_TO columns from 12HR to 24HR time (this code is for 2004-2010)

crimes04$TM_FM <- format(as.POSIXct(crimes04$TM_FM, format='%I:%M:%S %p'),
format = "%H:%M:%S")
crimes04$TM_TO <- format(as.POSIXct(crimes04$TM_TO, format='%I:%M:%S %p'),
format = "%H:%M:%S")

# Subset the data into the four crime types (this code is for 2004 - 2007)
assault04 <- crimes04 %>% filter(UCR %in% c("0410", "0420", "0430", "0440"))
burg04 <- crimes04 %>% filter(UCR %in% c("0511", "0521", "0531"))
gta04 <- crimes04 %>% filter(UCR %in% c("0710"))
robbery04 <- crimes04 %>% filter(UCR %in% c("0311", "0315", "0321", "0325", "0331",
"0335", "0341", "0345" ))

#this code is for 2008 - 2010. The UCR column is numeric
assault08 <- crimes08 %>% filter(UCR %in% c(410, 420, 430, 440))
burg08 <- crimes08 %>% filter(UCR %in% c(511, 521, 531))
gta08 <- crimes08 %>% filter(UCR %in% c(710))
robbery08 <- crimes08 %>% filter(UCR %in% c(311, 315, 321, 325, 331, 335, 341, 345))

# this code is for 2011 -2013
assault11 <- crimes11 %>% filter(MinOfucr %in% c(410, 420, 430, 440))
burg11 <- crimes11 %>% filter(MinOfucr %in% c(511, 521, 531))
gta11 <- crimes11 %>% filter(MinOfucr %in% c(710))
robbery11 <- crimes11 %>% filter(MinOfucr %in% c(311, 315, 321, 325, 331, 335, 341, 345))
```

```
# The blocks by neighborhood needs to be summarised by each census category retained
# the MED-AGE column contains zeros. accounted for with MED_AGE > 0 in the calculation
atl_nb <- atl_nb_blocks %>%
    group_by(NAME) %>%
    summarise(sum(POP2000), median(MED_AGE[MED_AGE > 0]), sum(OCCUPIED),
sum(HSE_UNITS),
        sum(VACANT), sum(OWNER_OCC))

#boxplots by neighborhood counts
boxplot(nb_attributes$assault04, nb_attributes$assault05, nb_attributes$assault06,
nb_attributes$assault07,
    nb_attributes$assault08, nb_attributes$assault09, nb_attributes$assault10,
nb_attributes$assault11,
    nb_attributes$assault12, nb_attributes$assault13, las = 1, main = "Boxplots for Aggravated
Assaults",
    ylab = "Number of Assaults", names = c("2004", "2005", "2006", "2007", "2008", "2009",
"2010", "2011", "2012", "2013"))

boxplot(nb_attributes$burg04, nb_attributes$burg05, nb_attributes$burg06,
nb_attributes$burg07,
    nb_attributes$burg08, nb_attributes$burg09, nb_attributes$burg10, nb_attributes$burg11,
    nb_attributes$burg12, nb_attributes$burg13, las = 1, main = "Boxplots for Burglary",
    ylab = "Number of Burglaries", names = c("2004", "2005", "2006", "2007", "2008", "2009",
"2010", "2011", "2012", "2013"))

boxplot(nb_attributes$gta04, nb_attributes$gta05, nb_attributes$gta06, nb_attributes$gta07,
```

```
    nb_attributes$gta08, nb_attributes$gta09, nb_attributes$gta10, nb_attributes$gta11,
    nb_attributes$gta12, nb_attributes$gta13, las = 1, main = "Boxplots for Auto Theft",
    ylab = "Number of Auto Thefts", names = c("2004", "2005", "2006", "2007", "2008",
"2009", "2010", "2011", "2012", "2013"))

boxplot(nb_attributes$robbery04, nb_attributes$robbery05, nb_attributes$robbery06,
nb_attributes$robbery07, nb_attributes$robbery08, nb_attributes$robbery09,
nb_attributes$robbery10, nb_attributes$robbery11, nb_attributes$robbery12,
nb_attributes$robbery13, las = 1, main = "Boxplots for Robbery",
    ylab = "Number of Robberies", names = c("2004", "2005", "2006", "2007", "2008", "2009",
"2010", "2011", "2012", "2013"))

## Rename columns in dfAtl2 to match remaining dfAtl1 columns
# This is to prep the second dataframe for rbind to create a single dataframe
colnames(df1)[colnames(df1) == "NEIGHBOURH"] <- "NEIGHBOURHOOD"
colnames(df1)[colnames(df1) == "INCIDENT_"] <- "INCIDENT_NUM"
colnames(df1)[colnames(df1) == "UCR_"] <- "UCR_CODE"
colnames(df2)[colnames(df2) == "offense_id"] <- "INCIDENT_NUM"
colnames(df2)[colnames(df2) == "rpt_date"] <- "RPT_DT"
colnames(df2)[colnames(df2) == "occur_date"] <- "DT_FM"
colnames(df2)[colnames(df2) == "occur_time"] <- "TM_FM"
colnames(df2)[colnames(df2) == "poss_date"] <- "DT_TO"
colnames(df2)[colnames(df2) == "poss_time"] <- "TM_TO"
colnames(df2)[colnames(df2) == "location"] <- "ADDRESS"
colnames(df2)[colnames(df2) == "MinOfucr"] <- "UCR_CODE"
colnames(df2)[colnames(df2) == "Shift"] <- "SHIFT"
colnames(df2)[colnames(df2) == "UC2.Literal"] <- "OFFENCE"
```

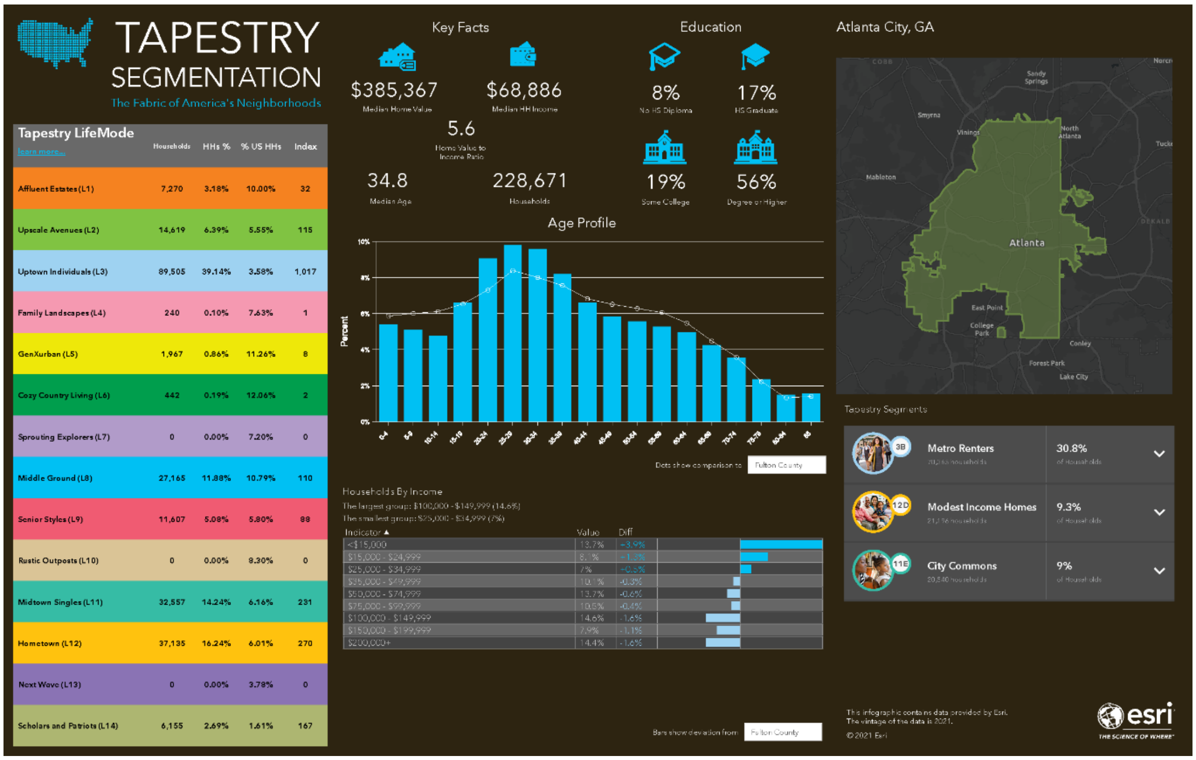
```
colnames(df2)[colnames(df2) == "neighborhood"] <- "NEIGHBOURHOOD"
colnames(df2)[colnames(df2) == "npu"] <- "NPU"
colnames(df2)[colnames(df2) == "x"] <- "X"
colnames(df2)[colnames(df2) == "y"] <- "Y"

## Convert dates to Date to extract the day of week information
df$RPT_DT <- as.Date(df$RPT_DT, format = "%m-%d-%Y")
df$DT_FM <- as.Date(df$DT_FM, format = '%m-%d-%Y')
df$DT_TO <- as.Date(df$DT_TO, format = '%m-%d-%Y')

# Create DAY_FM and DAY_TO columns in df2 so they match df1
# Populate with DOW information
df2$DAY_FM <- NA
df2$DAY_FM <- weekdays(df2$DT_FM, abbreviate = TRUE)
df2$DAY_TO <- NA
df2$DAY_TO <- weekdays(df2$DT_TO, abbreviate = TRUE)

#Combine both df1 and df2 into a single df
df <- rbind(df1, df2)

# Convert to POSIXct to do appropriate calculations later
# The extra step is to eliminate the time that would have been added if only used POSIXct
df$RPT_DT <- format(df$RPT_DT, format = "%m-%d=%Y")
df$RPT_DT <- as.POSIXct(df$RPT_DT, format = '%m-%d-%Y')
df$DT_FM <- format(df$DT_FM, format = "%m-%d=%Y")
df$DT_FM <- as.POSIXct(df$DT_FM, format = '%m-%d-%Y')
df$DT_TO <- format(df$DT_TO, format = "%m-%d=%Y")
```

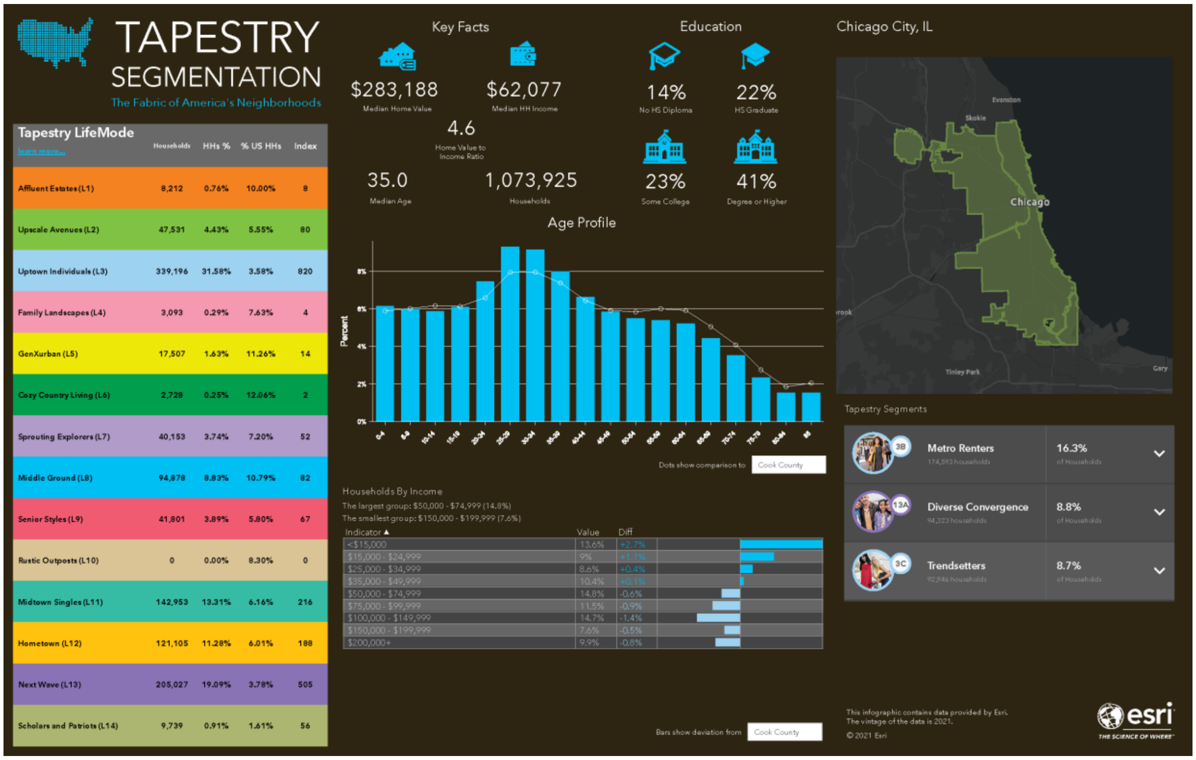
```r
df$DT_TO <- as.POSIXct(df$DT_TO, format = '%m-%d-%Y')

# Once the completed data frame (our tidy crime data) is finished
# subset into two year sections 2004-2009 and 2010-2013.
# This is to do stats according to the census-related data.
## Check for any NAs
colSums(is.na(df))

#/////////////////////////////////////////////////////////////

crimesNPU <- read_csv("npuCityCrime.csv", col_names = TRUE)
colnames(crimesNPU)[colnames(crimesNPU) == "X1"] <- "NPU"
crimesNPUYear <- crimesNPUYear %>% select(-c(1)) # To delete the first column (X1)

# After making characters factors... create unique values for each level (so to speak), otherwise
# will have duplicates. Since we will do many plots using the NPU, we will do this there.
crimesNPUYear$NPU <- factor(crimesNPUYear$NPU, levels =
sort(unique(crimesNPUYear$NPU), ordered = TRUE))

#npuLandArea <- read.table("npuLandArea.txt", header = TRUE, sep = ",", stringsAsFactors =
FALSE)

# Split crimesNPUYear into two sets: 2004-2008 and 2009-2013
crimesNPUYr1 <- crimesNPUYear %>%
	filter(YEAR <= 2008)
crimesNPUYr2 <- crimesNPUYear %>%
	filter(YEAR >= 2009)
```

```
# Save files
save(crimesNPUYear, file = "npuCrimebyYr.Rdata")
save(crimesNPUYr1, file = "npuCrimebyYr1.Rdata")
save(crimesNPUYr2, file = "npuCrimebyYr2.Rdata")

################################################
#
#  Import and Merge relevant files with NPU crimes file
#
################################################

npuPop <- read_csv("npuPop.csv", col_names = TRUE)
npuSocioEcon <- read_csv("npuSocioEcon.csv", col_names = TRUE)

# This ensures import of data with large number and 6 decimal points

options(digits = 15)
npuLandArea <- read_csv("npuLandArea.csv", col_names = TRUE)

# Merge data frames
npuStats <- merge(npuPop, crimesNPU, by = "NPU")
npuStats <- merge(npuStats, npuSocioEcon, by = "NPU")
npuStats <- merge(npuStats, npuLandArea, by = "NPU")
```

Appendix B

ESRI Tapestry Segmentation




TAPESTRY
SEGMENTATION
The Fabric of America's Neighborhoods
Tapestry LifeMode
Households | HHs % | % US HHs | Index
Affluent Estates (L1) 8,212 0.76% 10.00% 8
Upscale Avenues (L2) 47,531 4.43% 5.55% 80
Uptown Individuals (L3) 339,196 31.58% 3.58% 820
Family Landscapes (L4) 3,093 0.29% 7.63% 4
GenXurban (L5) 17,507 1.63% 11.26% 14
Cozy Country Living (L6) 2,728 0.25% 12.06% 2
Sprouting Explorers (L7) 40,153 3.74% 7.20% 52
Middle Ground (L8) 94,878 8.83% 10.79% 82
Senior Styles (L9) 41,801 3.89% 5.80% 67
Rustic Outposts (L10) 0 0.00% 8.30% 0
Midtown Singles (L11) 142,953 13.31% 6.16% 216
Hometown (L12) 121,105 11.28% 6.01% 188
Next Wave (L13) 205,027 19.09% 3.78% 505
Scholars and Patriots (L14) 9,739 0.91% 1.61% 56
Key Facts
$283,188 Median Home Value
$62,077 Median HH Income
4.6 Home Value to Income Ratio
35.0 Median Age
1,073,925 Households
Education
14% No HS Diploma
22% HS Graduate
23% Some College
41% Degree or Higher
Age Profile
Percent
Dots show comparison to Cook County
Households By Income
The largest group: $50,000 - $74,999 (14.8%)
The smallest group: $150,000 - $199,999 (7.6%)
Indicator Value Diff
<$15,000 13.6% +2.7%
$15,000 - $24,999 9% +1.1%
$25,000 - $34,999 8.6% +0.4%
$35,000 - $49,999 10.4% +0.1%
$50,000 - $74,999 14.8% -0.6%
$75,000 - $99,999 11.5% -0.9%
$100,000 - $149,999 14.7% -1.4%
$150,000 - $199,999 7.6% -0.5%
$200,000+ 9.9% -0.8%
Bars show deviation from Cook County
Chicago City, IL
Evanston
Skokie
Chicago
Tinley Park
Gary
Tapestry Segments
Metro Renters 16.3% of Households
Diverse Convergence 8.8% of Households
Trendsetters 8.7% of Households
This infographic contains data provided by Esri.
The vintage of the data is 2021.
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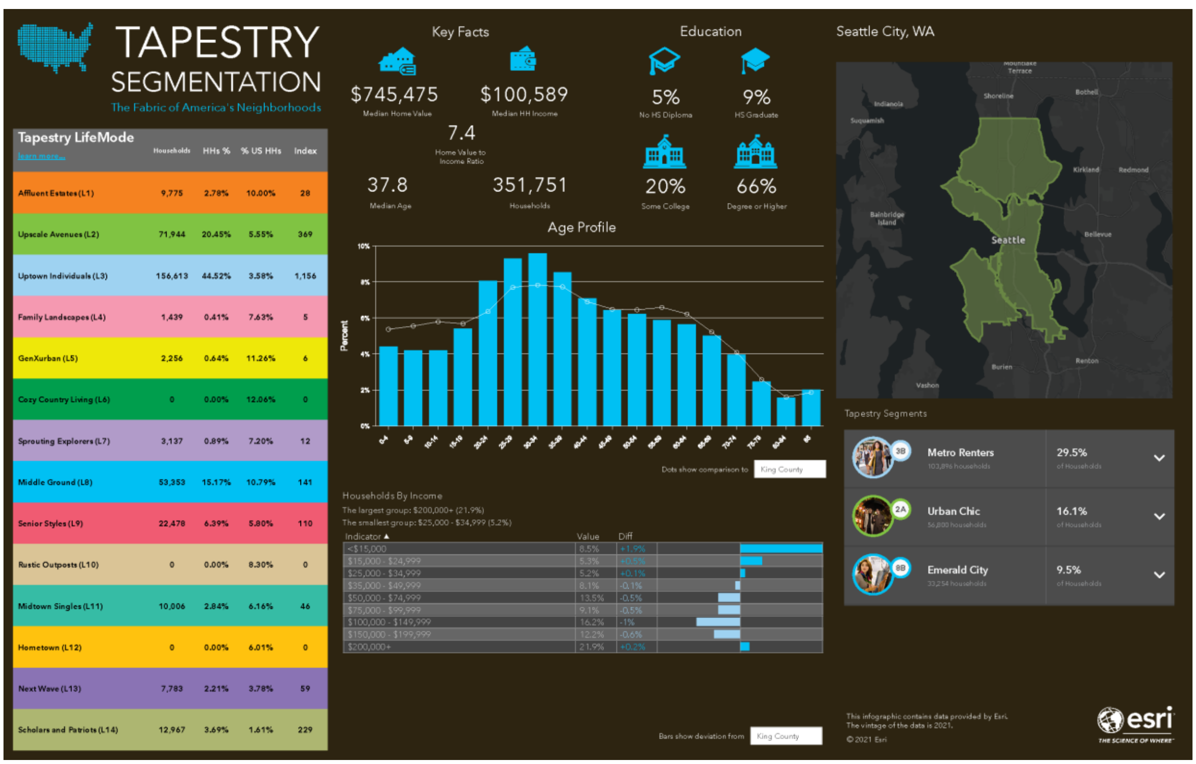
TAPESTRY
SEGMENTATION
The Fabric of America's Neighborhoods
Tapestry LifeMode
Households | HHs % | % US HHs | Index
Affluent Estates (L1) 9,775 2.78% 10.00% 28
Upscale Avenues (L2) 71,944 20.45% 5.55% 369
Uptown Individuals (L3) 156,613 44.52% 3.58% 1,156
Family Landscapes (L4) 1,439 0.41% 7.63% 5
GenXurban (L5) 2,256 0.64% 11.26% 6
Cozy Country Living (L6) 0 0.00% 12.06% 0
Sprouting Explorers (L7) 3,137 0.89% 7.20% 12
Middle Ground (L8) 53,353 15.17% 10.79% 141
Senior Styles (L9) 22,478 6.39% 5.80% 110
Rustic Outposts (L10) 0 0.00% 8.30% 0
Midtown Singles (L11) 10,006 2.84% 6.16% 46
Hometown (L12) 0 0.00% 6.01% 0
Next Wave (L13) 7,783 2.21% 3.78% 59
Scholars and Patriots (L14) 12,967 3.69% 1.61% 229
Key Facts
$745,475 Median Home Value
$100,589 Median HH Income
7.4 Home Value to Income Ratio
37.8 Median Age
351,751 Households
Education
5% No HS Diploma
9% HS Graduate
20% Some College
66% Degree or Higher
Age Profile
Percent
Dots show comparison to King County
Households By Income
The largest group: $200,000+ (21.9%)
The smallest group: $25,000 - $34,999 (5.2%)
Indicator Value Diff
<$15,000 8.5% +1.9%
$15,000 - $24,999 5.3% +0.5%
$25,000 - $34,999 5.2% +0.1%
$35,000 - $49,999 8.1% -0.1%
$50,000 - $74,999 13.5% -0.5%
$75,000 - $99,999 9.1% -0.5%
$100,000 - $149,999 16.2% -1%
$150,000 - $199,999 12.2% -0.6%
$200,000+ 21.9% +0.2%
Bars show deviation from King County
Seattle City, WA
Shoreline
Bothell
Kirkland
Redmond
Seattle
Bellevue
Burien
Renton
Tapestry Segments
Metro Renters 29.5% of Households
Urban Chic 16.1% of Households
Emerald City 9.5% of Households
This infographic contains data provided by Esri.
The vintage of the data is 2021.
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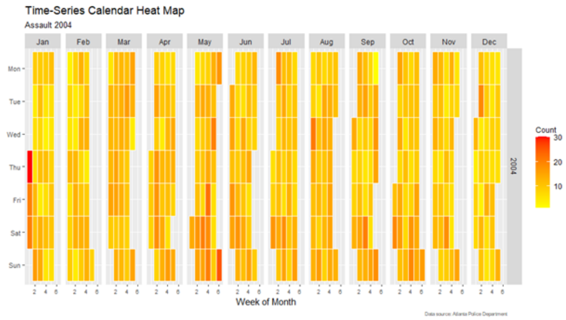
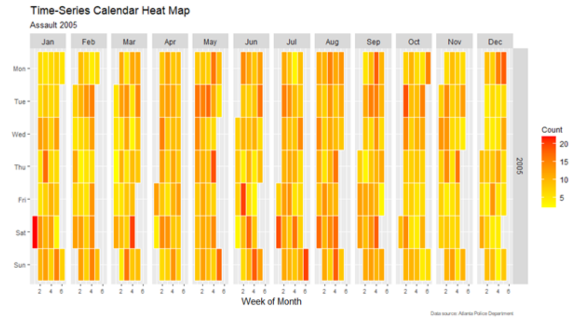
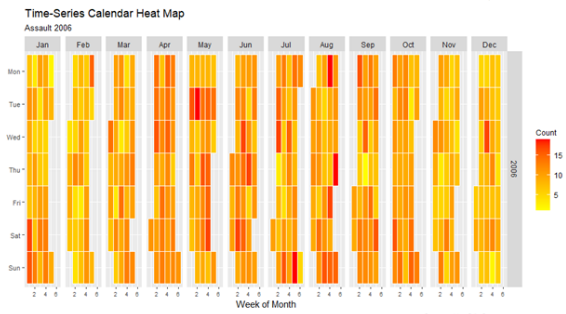
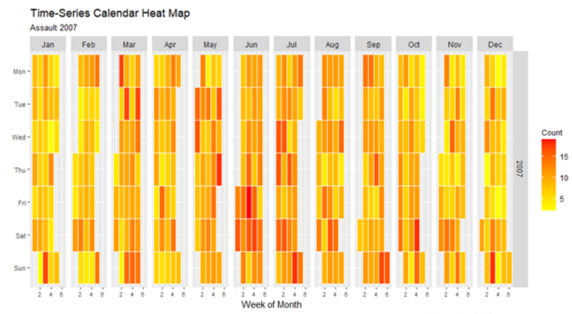
Appendix C

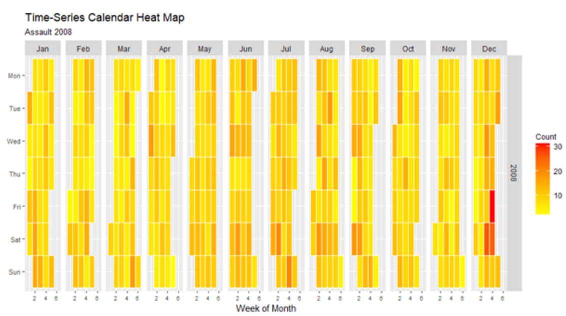
Atlanta Calendar Timeseries Heatmaps

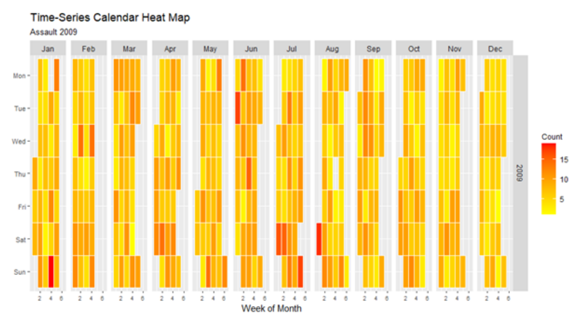


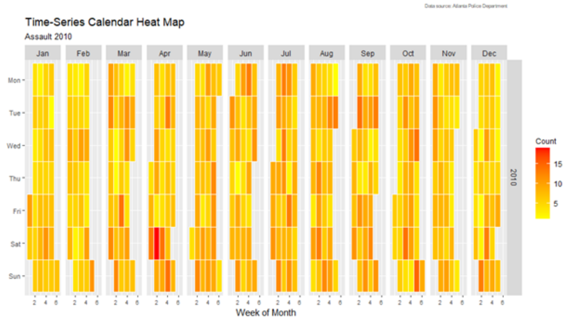


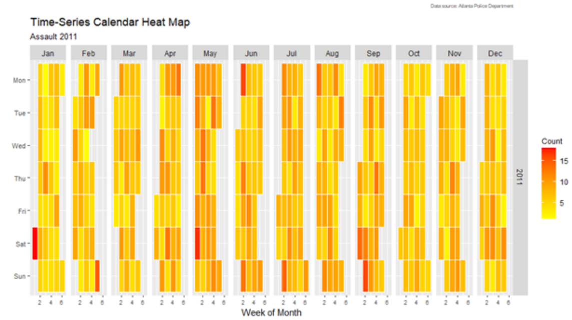


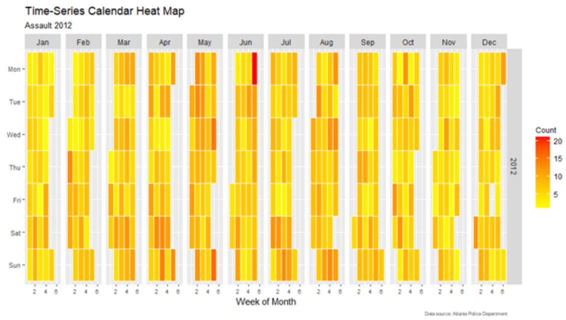


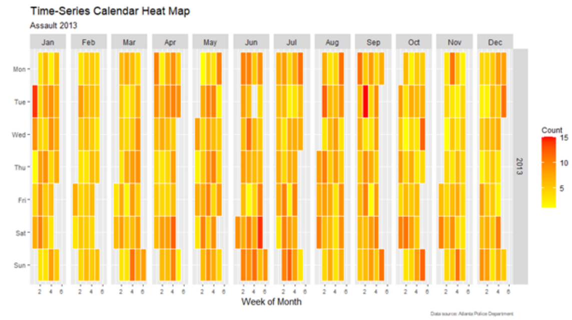


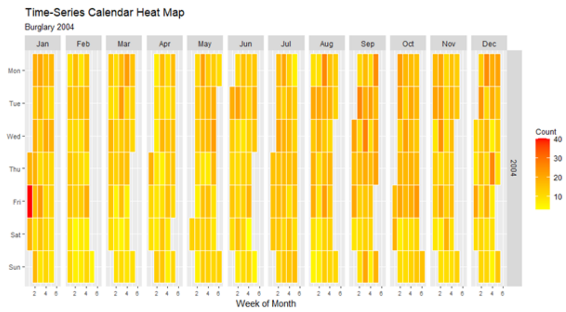


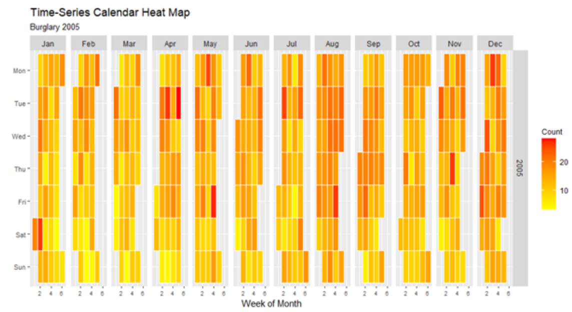


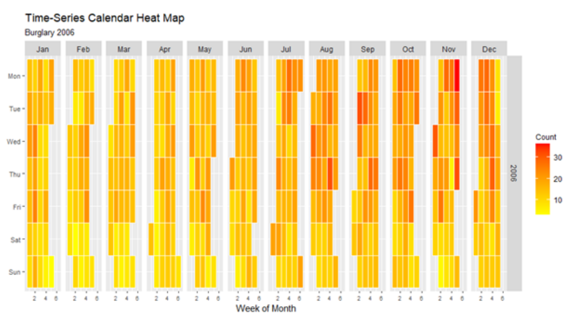


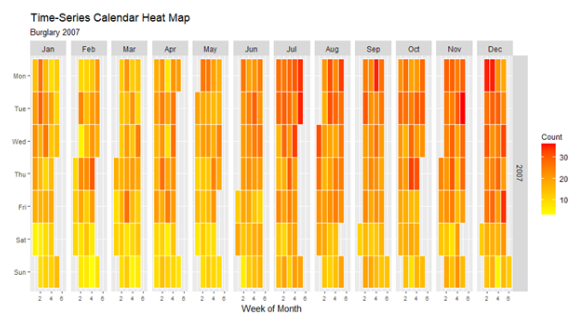

Time-Series Calendar Heat Map
Assault 2012
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
20 15 10 5
2012
Week of Month

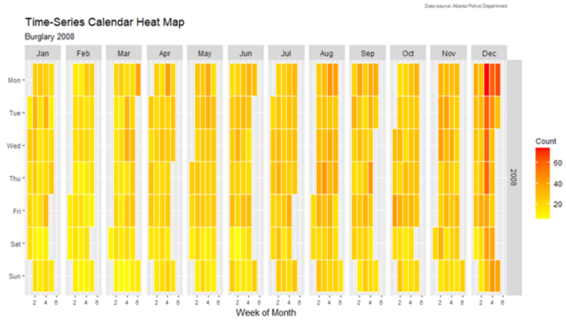

Time-Series Calendar Heat Map
Assault 2013
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
15 10 5
2013
Week of Month

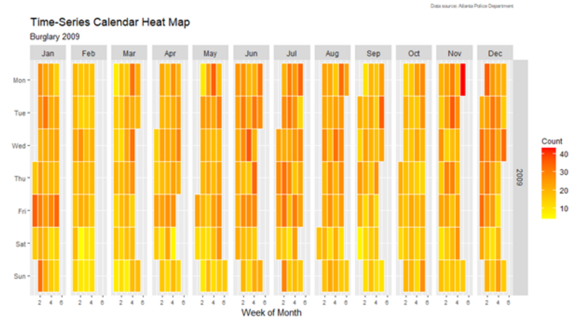

Time-Series Calendar Heat Map
Burglary 2004
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
40 30 20 10
2004
Week of Month

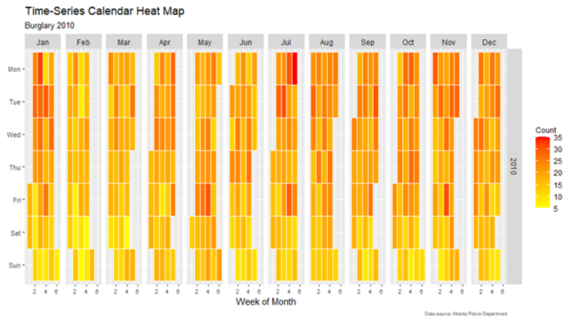

Time-Series Calendar Heat Map
Burglary 2005
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
20 10
2005
Week of Month

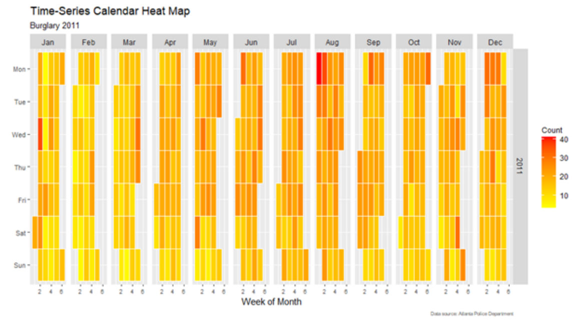

Time-Series Calendar Heat Map
Burglary 2006
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
30 20 10
2006
Week of Month

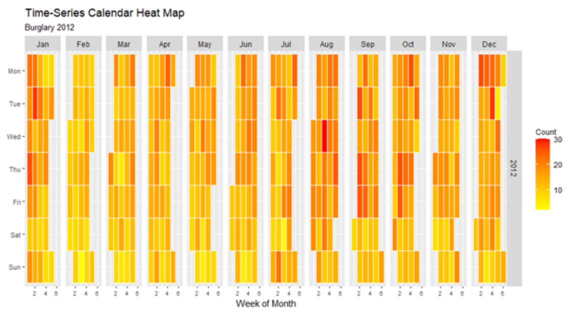

Time-Series Calendar Heat Map
Burglary 2007
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
30 20 10
2007
Week of Month

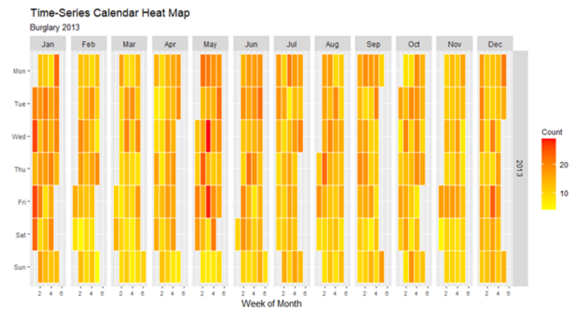

Time-Series Calendar Heat Map
Burglary 2008
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
60 40 20
2008
Week of Month

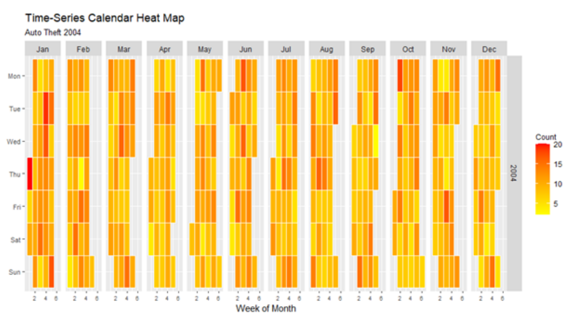

Time-Series Calendar Heat Map
Burglary 2009
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
40 30 20 10
2009
Week of Month

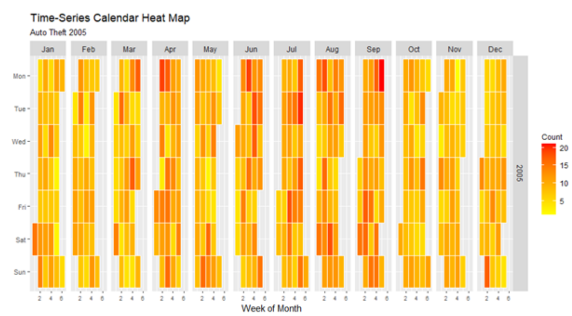

Time-Series Calendar Heat Map
Burglary 2010
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
35 30 25 20 15 10 5
2010
Week of Month

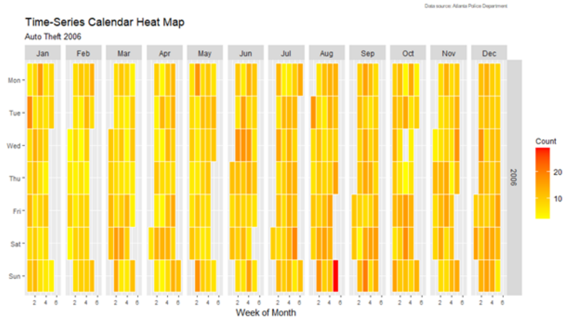

Time-Series Calendar Heat Map
Burglary 2011
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
40 30 20 10
2011
Week of Month


Time-Series Calendar Heat Map
Burglary 2012
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
30 20 10
2012
Week of Month


Time-Series Calendar Heat Map
Burglary 2013
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
20 10
2013
Week of Month


Time-Series Calendar Heat Map
Auto Theft 2004
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
20 15 10 5
2004
Week of Month


Time-Series Calendar Heat Map
Auto Theft 2005
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
20 15 10 5
2005
Week of Month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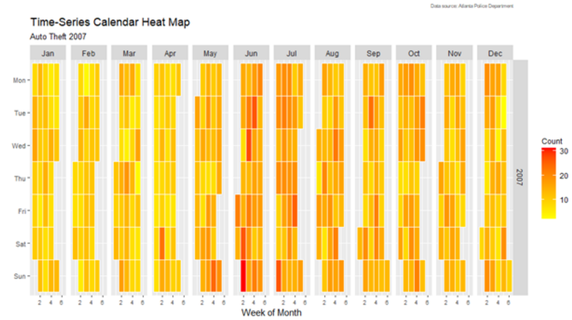
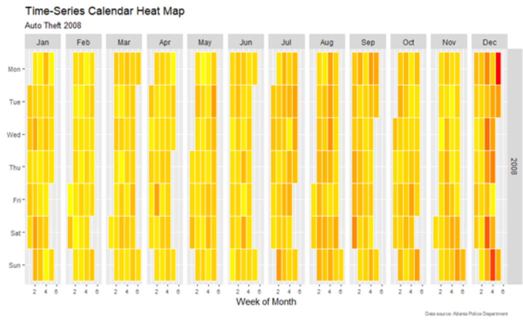
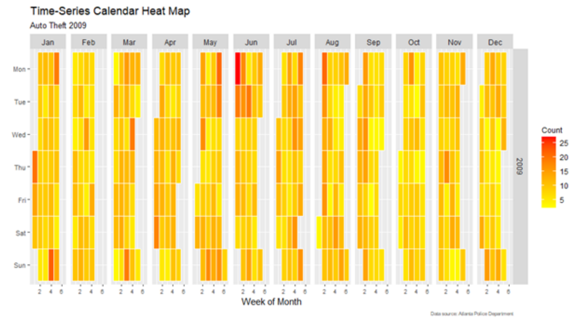
Auto Theft 2006
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
20 10
2006
Week of Month


Time-Series Calendar Heat Map
Auto Theft 2007
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
30 20 10
2007
Week of Month


Time-Series Calendar Heat Map
Auto Theft 2008
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
40
30
20
10
2008
Week of Month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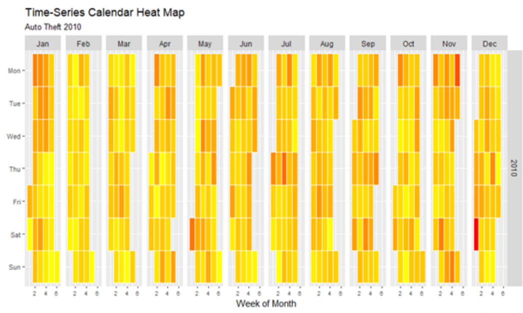
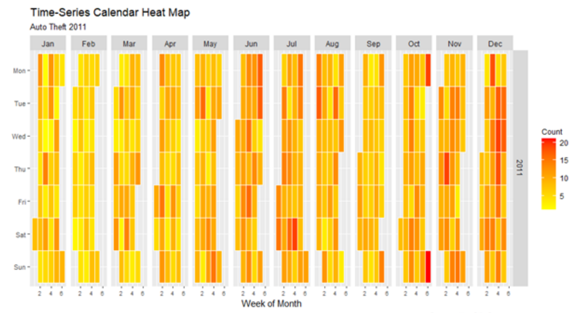
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
25
20
15
10
5
2009
Week of Month


Time-Series Calendar Heat Map
Auto Theft 2010
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
20
15
10
5
2010
Week of Month


Time-Series Calendar Heat Map
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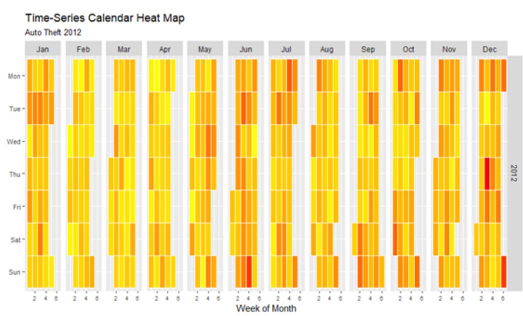
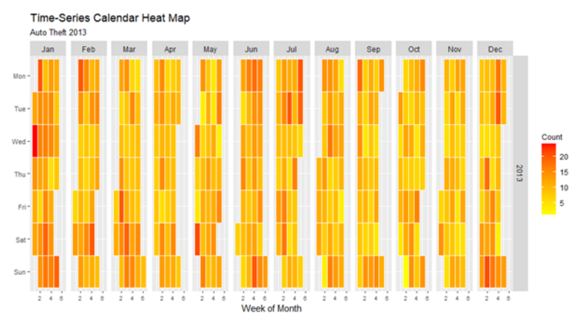
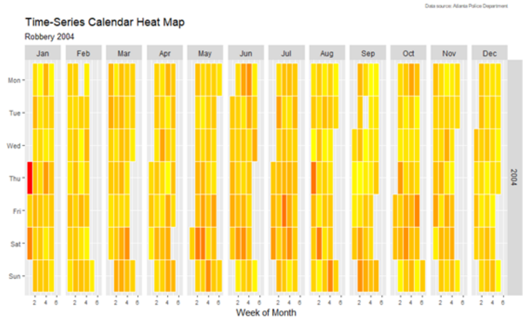
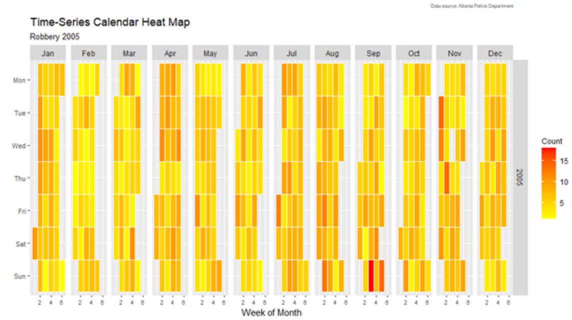
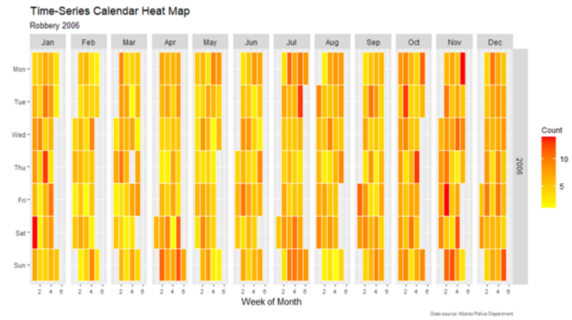
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
20
15
10
5
2011
Week of Month

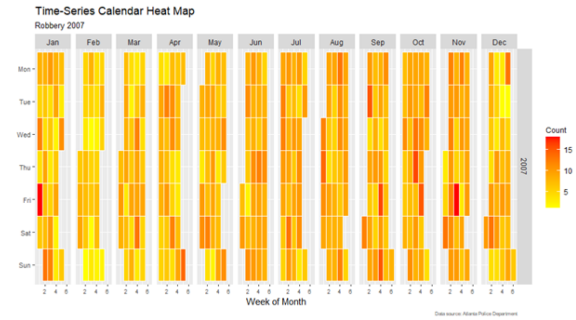

Time-Series Calendar Heat Map
Auto Theft 2012
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
30
20
10
2012
Week of Month

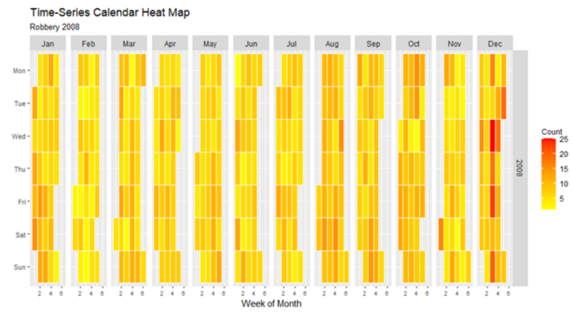

Time-Series Calendar Heat Map
Auto Theft 2013
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
20
15
10
5
2013
Week of Month

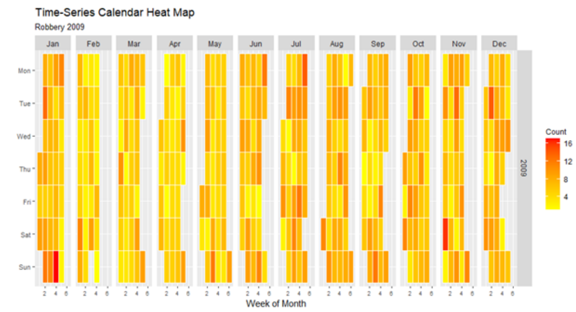

Time-Series Calendar Heat Map
Robbery 2004
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
20
15
10
5
2004
Week of Month

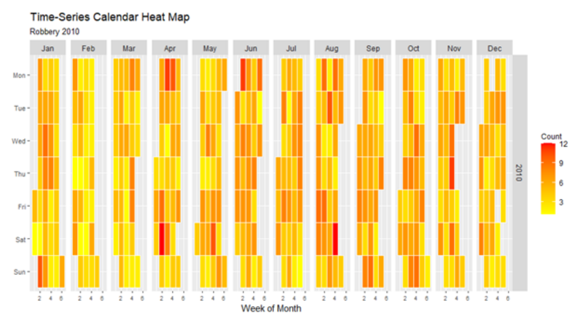

Time-Series Calendar Heat Map
Robbery 2005
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
15
10
5
2005
Week of Month

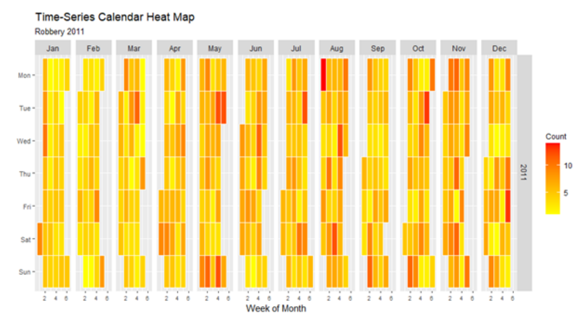

Time-Series Calendar Heat Map
Robbery 2006
Week of Month
Count

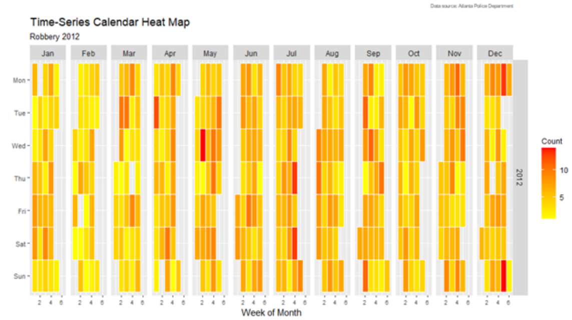

Time-Series Calendar Heat Map
Robbery 2007
Week of Month
Count

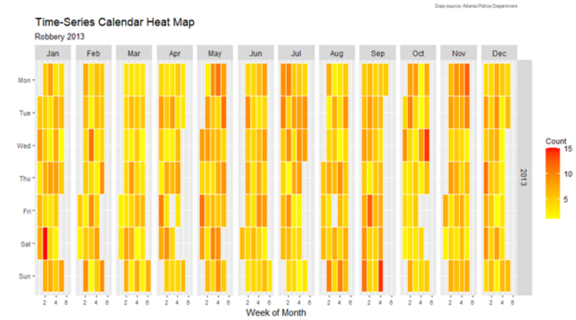

Time-Series Calendar Heat Map
Robbery 2008
Week of Month
Count


Time-Series Calendar Heat Map
Robbery 2009
Week of Month
Count

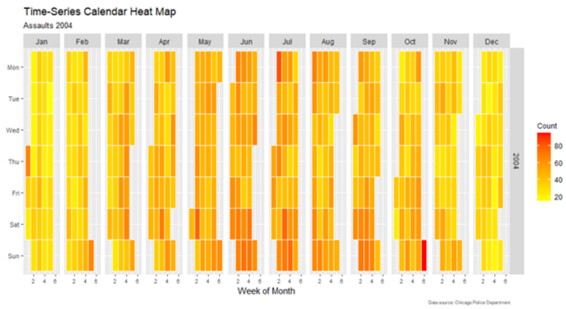

Time-Series Calendar Heat Map
Robbery 2010
Week of Month
Count

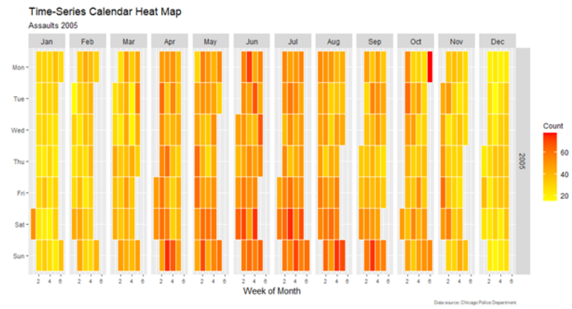

Time-Series Calendar Heat Map
Robbery 2011
Week of Month
Count

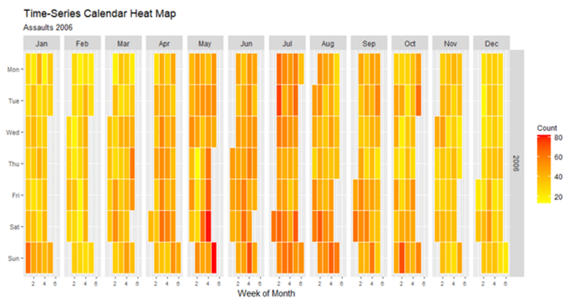

Time-Series Calendar Heat Map
Robbery 2012
Week of Month
Count

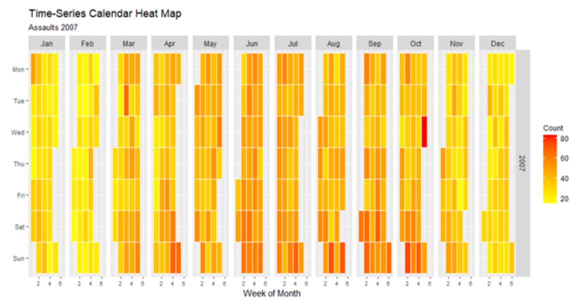

Time-Series Calendar Heat Map
Robbery 2013
Week of Month
Count

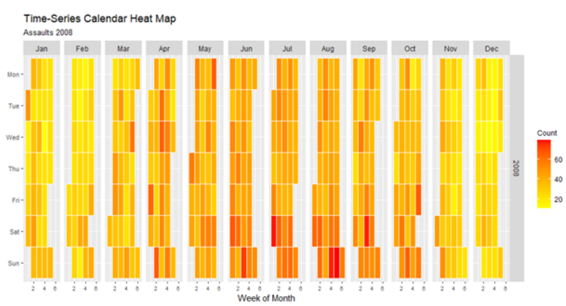
Chicago Timeseries Heatmaps

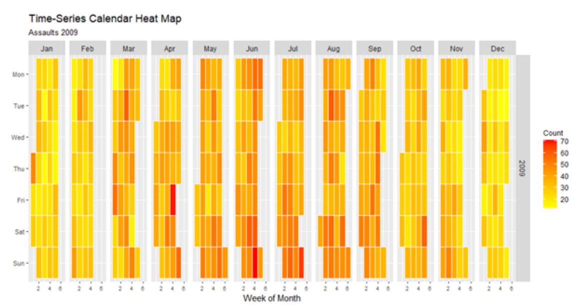


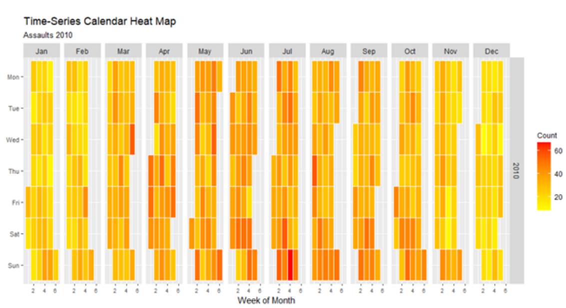


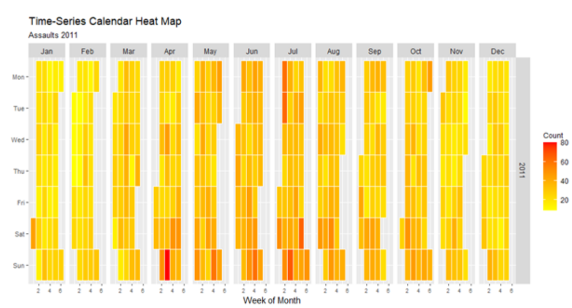


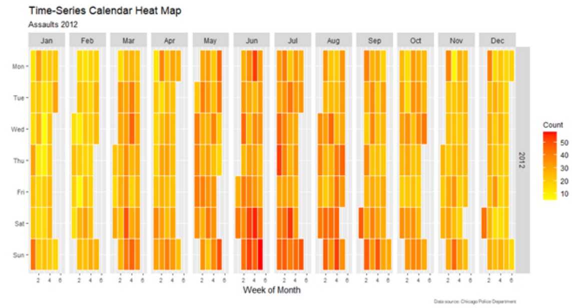


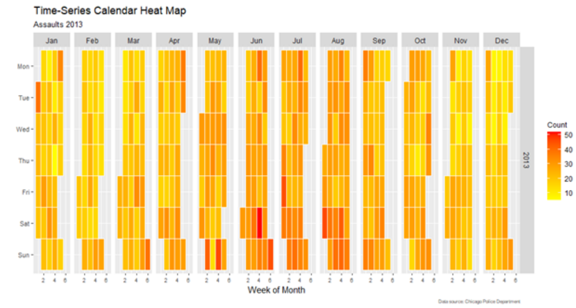


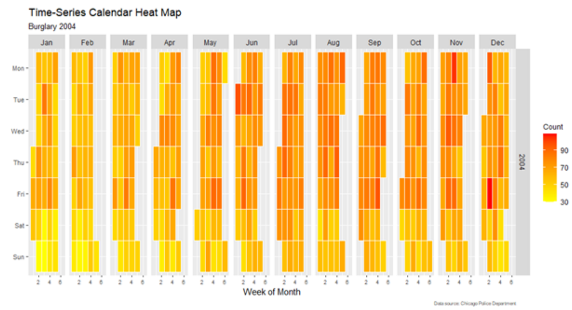


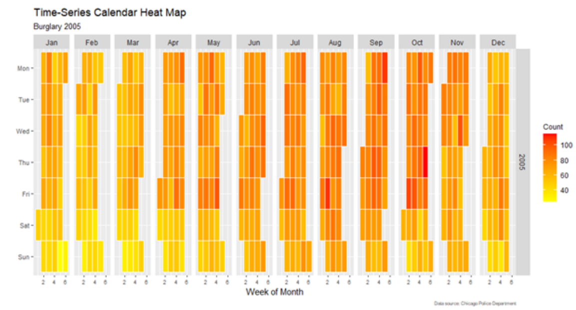





Time-Series Calendar Heat Map
Assaults 2012
Count
Week of Month


Time-Series Calendar Heat Map
Assaults 2013
Count
Week of Month


Time-Series Calendar Heat Map
Burglary 2004
Count
Week of Month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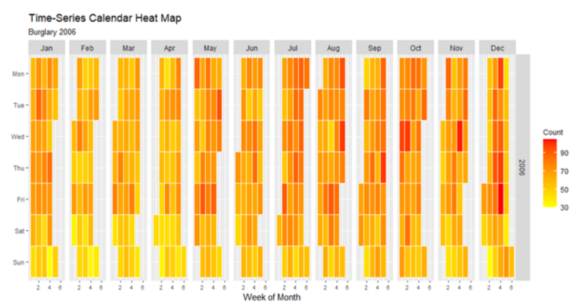
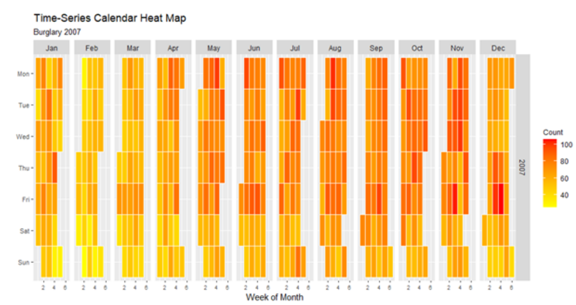
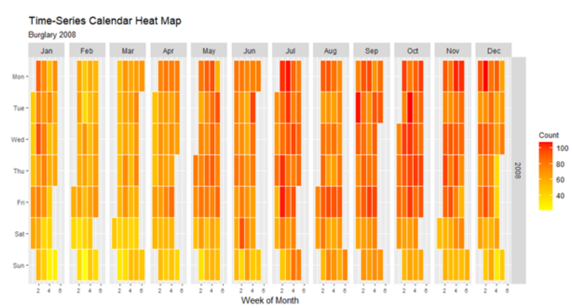
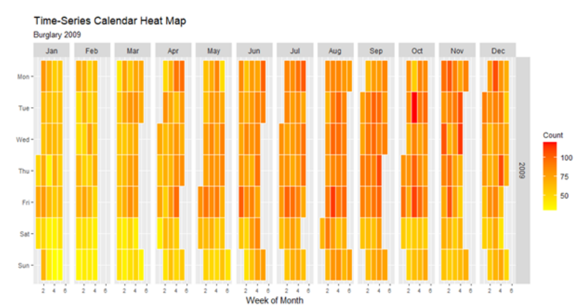
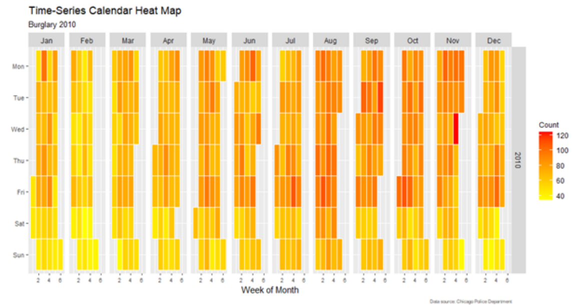
Burglary 2005
Count
Week of Month

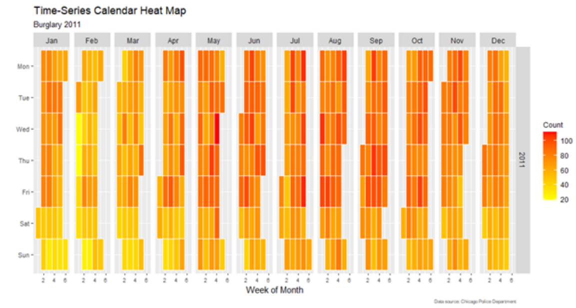

Time-Series Calendar Heat Map
Burglary 2006
Count
Week of Month


Time-Series Calendar Heat Map
Burglary 2007
Count
Week of Month


Time-Series Calendar Heat Map
Burglary 2008
Count
Week of Month


Time-Series Calendar Heat Map
Burglary 2009
Count
Week of Month


Time-Series Calendar Heat Map
Burglary 2010
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
120 100 80 60 40
2010
Week of Month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Count
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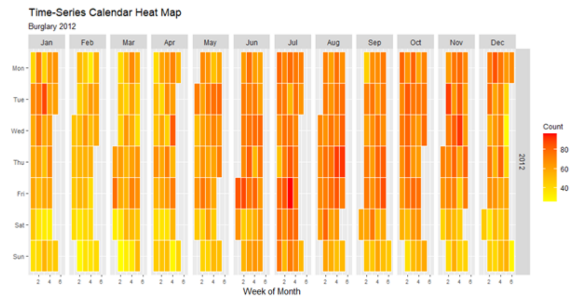
2011
Week of Month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Count
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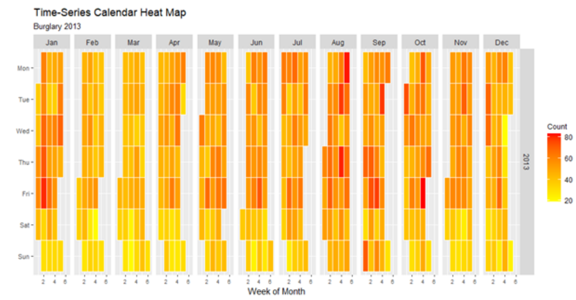
2012
Week of Month


Time-Series Calendar Heat Map
Burglary 2013
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Mon Tue Wed Thu Fri Sat Sun
Count
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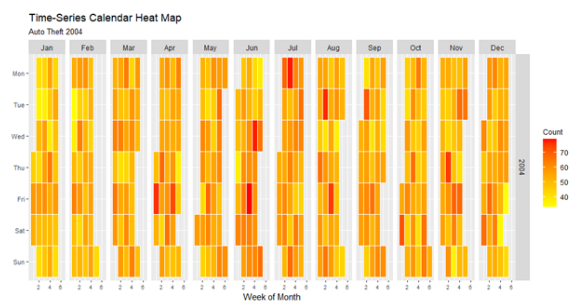
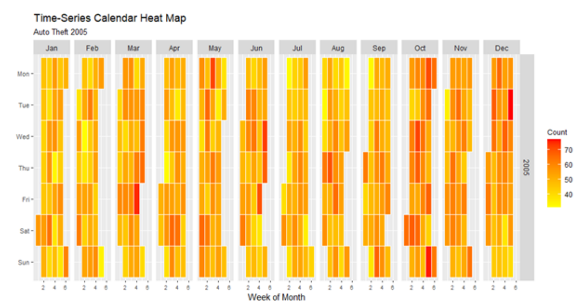
2013
Week of Month


Time-Series Calendar Heat Map
Auto Theft 2004
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Mon Tue Wed Thu Fri Sat Sun
Count
70 60 50 40
2004
Week of Month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Mon Tue Wed Thu Fri Sat Sun
Count
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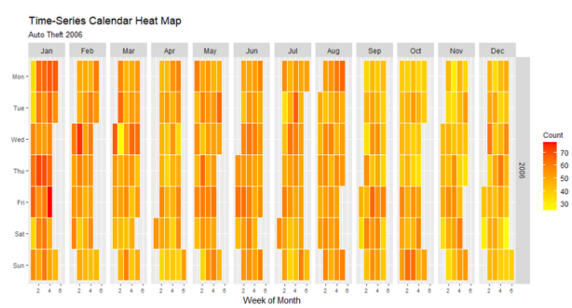
2005
Week of Month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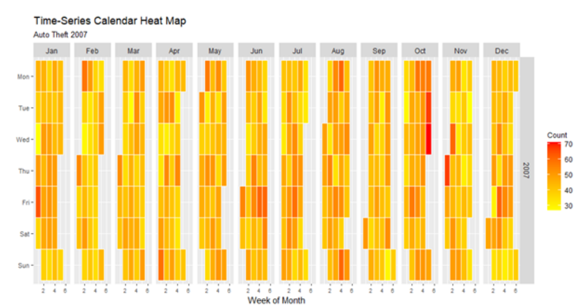
Mon Tue Wed Thu Fri Sat Sun
Count
70 60 50 40 30
2006
Week of Month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Auto Theft 2007
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Mon Tue Wed Thu Fri Sat Sun
Count
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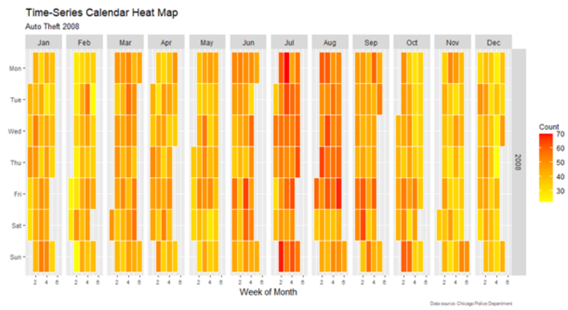
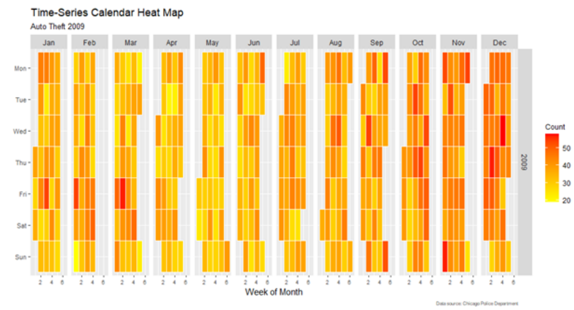
2007
Week of Month


Time-Series Calendar Heat Map
Auto Theft 2008
Week of Month
Count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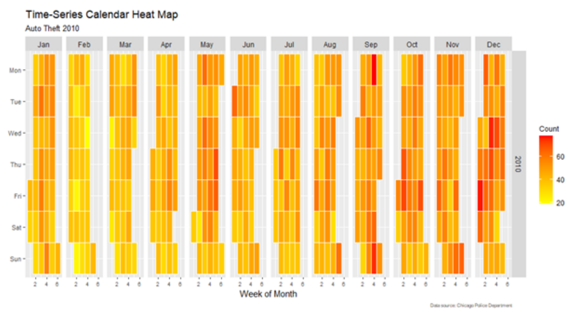
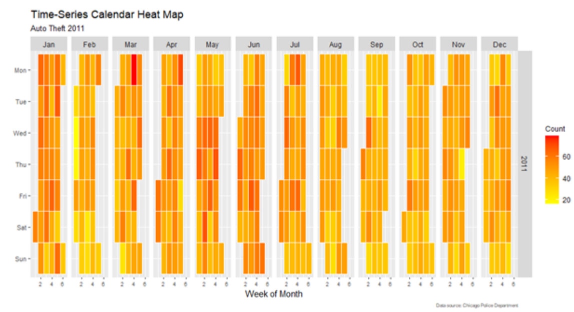
Auto Theft 2009
Week of Month
Count


Time-Series Calendar Heat Map
Auto Theft 2010
Week of Month
Count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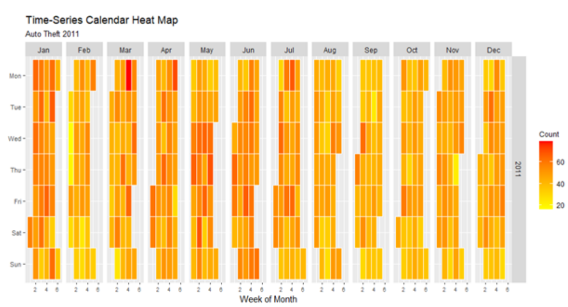
Auto Theft 2011
Week of Month
Count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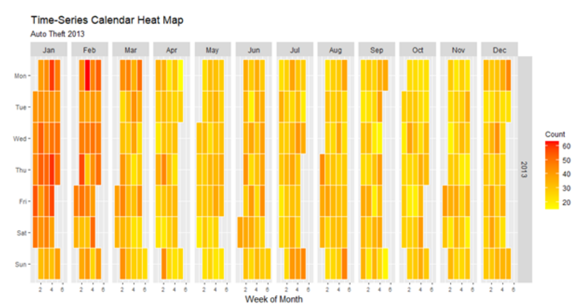
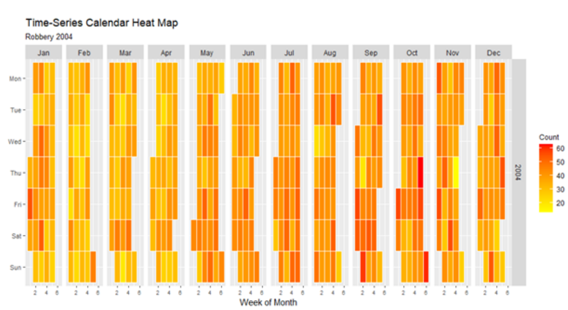
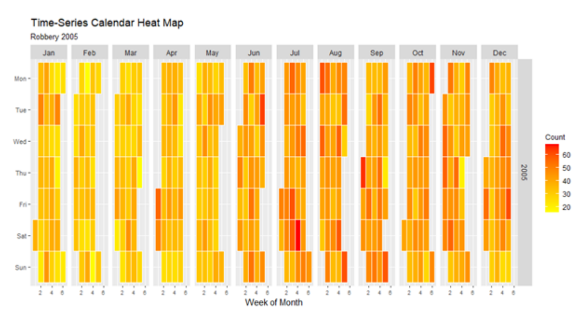
Auto Theft 2011
Week of Month
Count


Time-Series Calendar Heat Map
Auto Theft 2013
Week of Month
Count


Time-Series Calendar Heat Map
Robbery 2004
Week of Month
Count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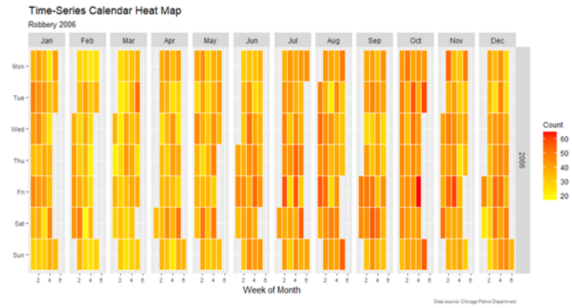
Robbery 2005
Week of Month
Count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Robbery 2006
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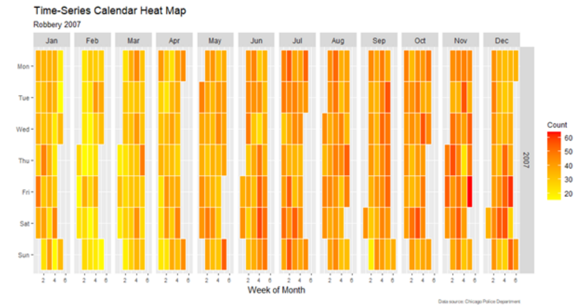
Mon Tue Wed Thu Fri Sat Sun
Count 60 50 40 30 20
2006
Week of Month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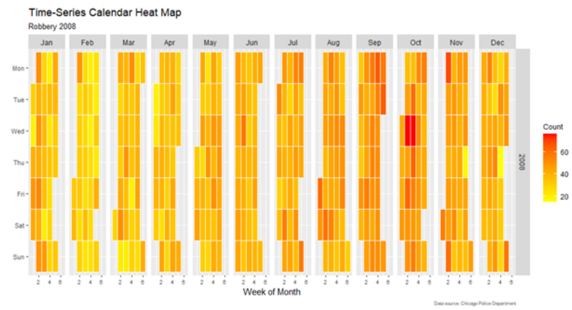
2007
Week of Month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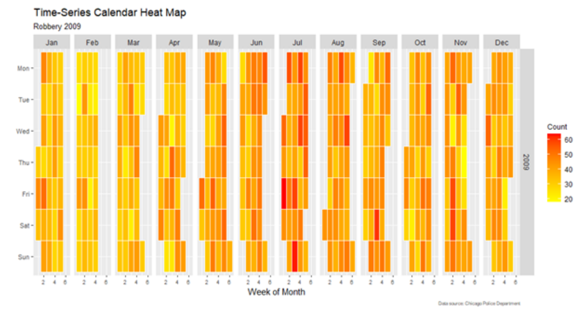
Mon Tue Wed Thu Fri Sat Sun
Count 60 40 20
2008
Week of Month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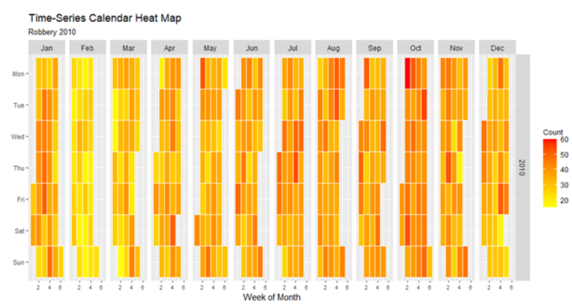
2009
Week of Month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Mon Tue Wed Thu Fri Sat Sun
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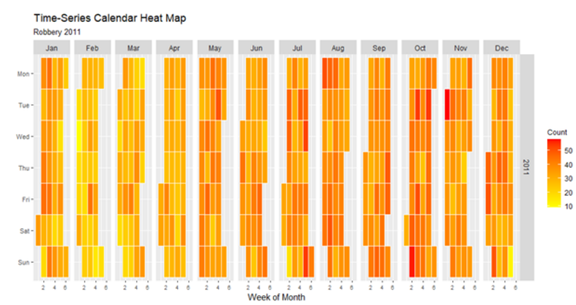
2010
Week of Month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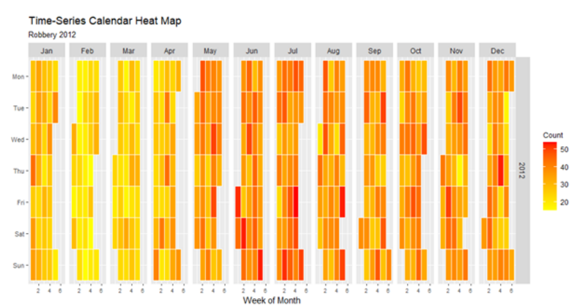
2011
Week of Month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Robbery 2012
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Mon Tue Wed Thu Fri Sat Sun
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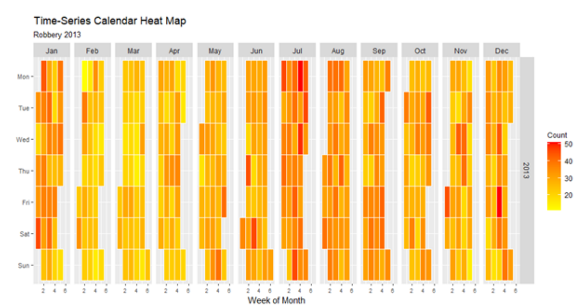
2012
Week of Month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Robbery 2013
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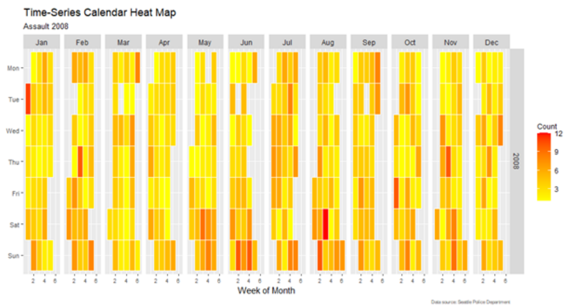
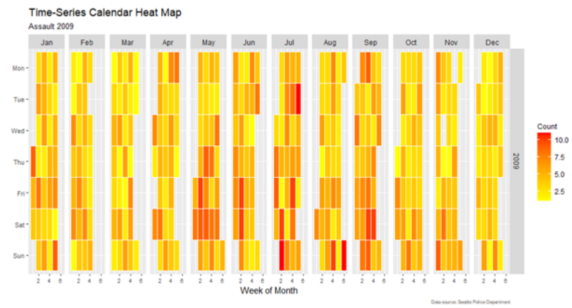
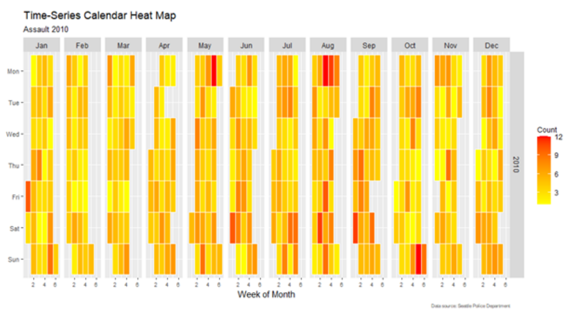
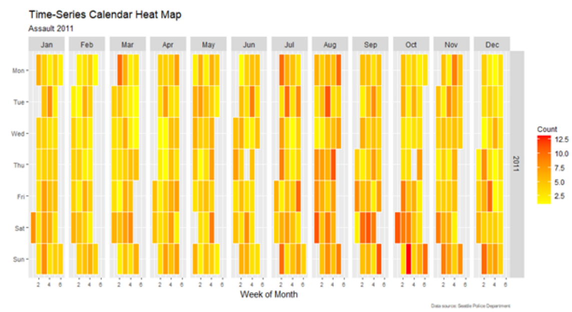
Mon Tue Wed Thu Fri Sat Sun
Count 50 40 30 20
2013
Week of Month

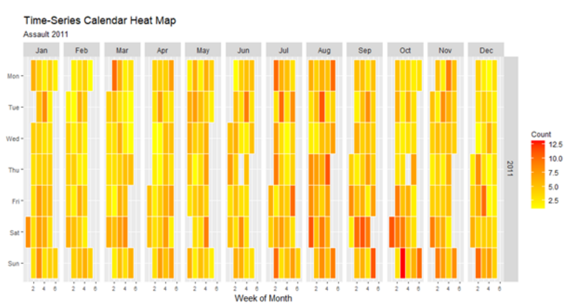
Seattle Timeseries Heatmaps

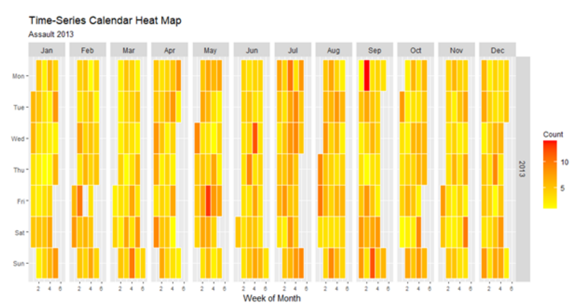


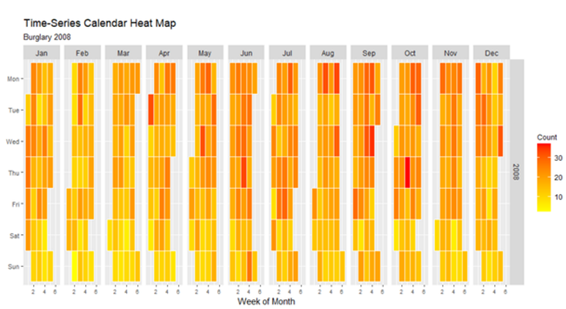


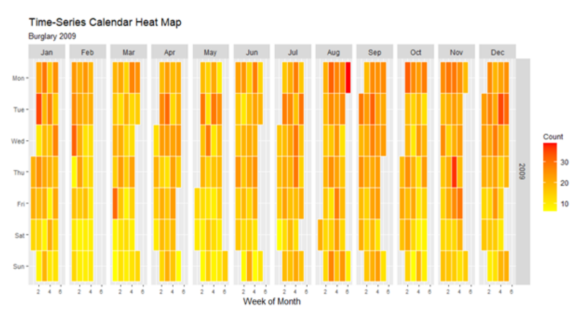


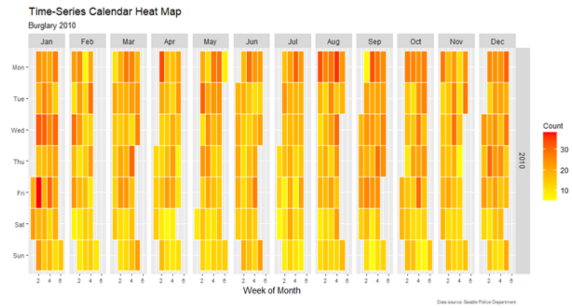


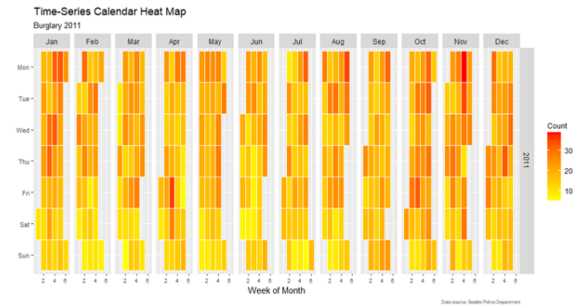


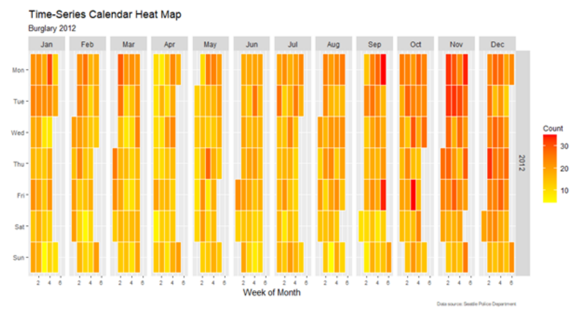







Time-Series Calendar Heat Map
Burglary 2010
Week of Month
Count


Time-Series Calendar Heat Map
Burglary 2011
Week of Month
Count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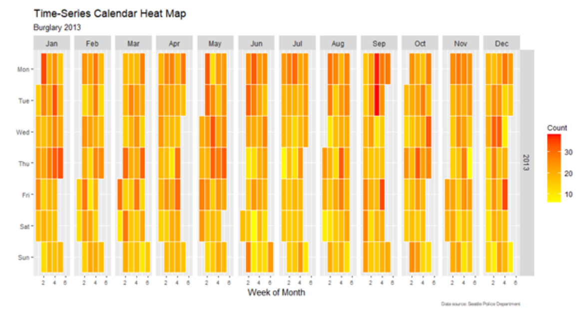
Burglary 2012
Week of Month
Count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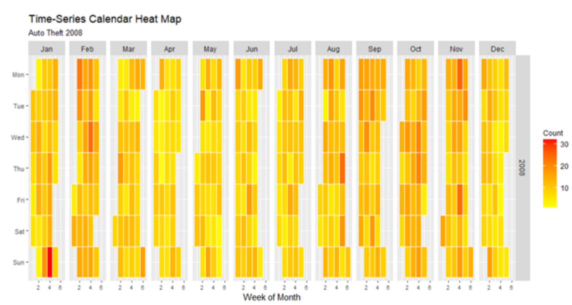
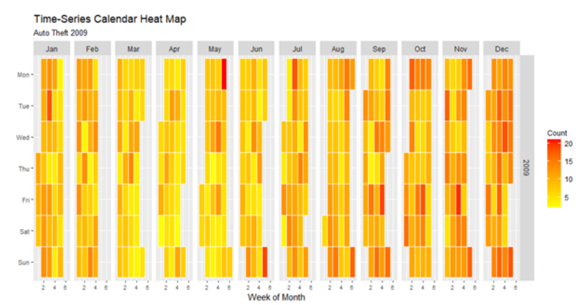
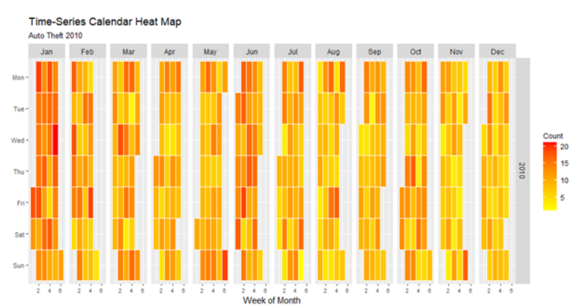
Burglary 2013
Week of Month
Count


Time-Series Calendar Heat Map
Auto Theft 2008
Week of Month
Count


Time-Series Calendar Heat Map
Auto Theft 2009
Week of Month
Count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Auto Theft 2010
Week of Month
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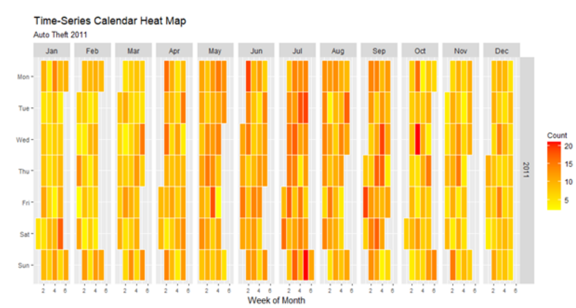
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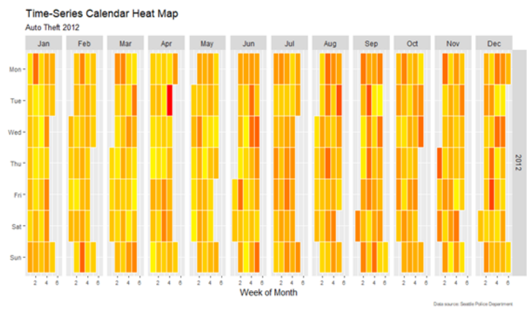
Auto Theft 2011
Week of Month
Count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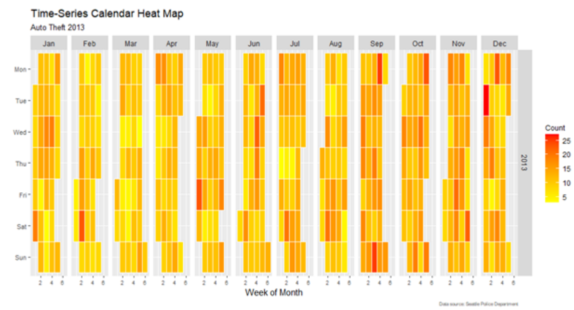
Auto Theft 2012
Week of Month
Count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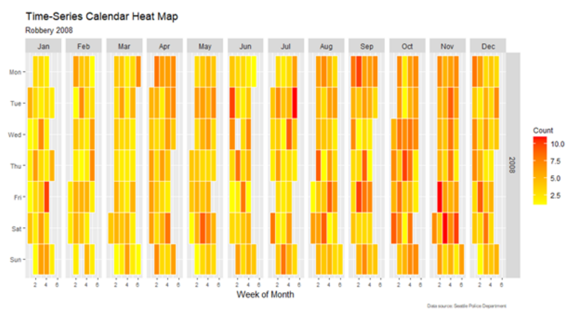
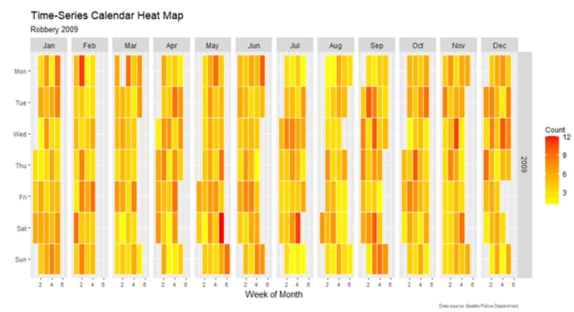
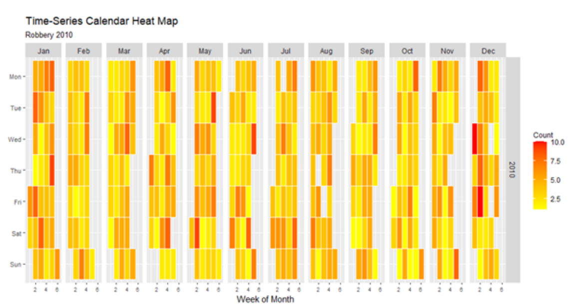
Auto Theft 2013
Week of Month
Count


Time-Series Calendar Heat Map
Robbery 2008
Week of Month
Count


Time-Series Calendar Heat Map
Robbery 2009
Week of Month
Count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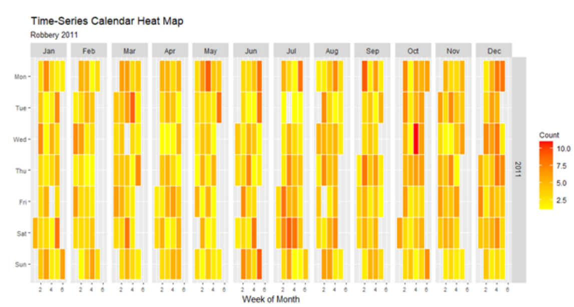
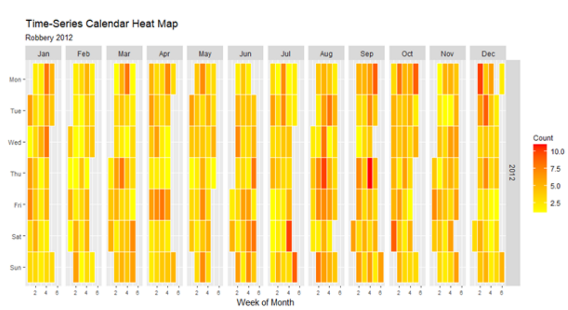
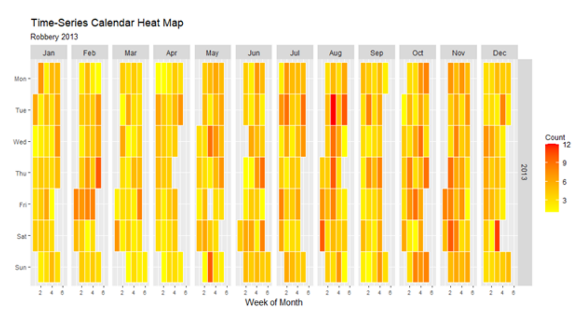
Robbery 2010
Week of Month
Count


Time-Series Calendar Heat Map
Robbery 2011
Week of Month
Count


Time-Series Calendar Heat Map
Robbery 2012
Week of Month
Count


Time-Series Calendar Heat Map
Robbery 2013
Week of Month
Count