INVESTIGATING THE SPATIOTEMPORAL DISTRIBUTION AND ENVIRONMENTAL RISK FACTORS OF HARM-WEIGHTED CRIME

by

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DEDICATION

I would like to dedicate this dissertation to my Mamá, Haydee C. Hensley.

Desde el primer día, tú has sido mi mayor admiradora y espero que sepas que te quiero mucho. Ahora puedes llamarme, ‘mi nieta, la Doctora.’ Te quiero *mucho*, your VIG.

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ABSTRACT

BACKGROUND

Due to the recent, extensive use of geospatial information systems (GIS), questions about spatial criminology can be answered in greater detail than they have been in the past. However, most of this research is focused on single crime categories, or only examines these offenses as if each offense held the same weight relative to the amount of harm that is caused. There are still questions that have not been answered, specifically regarding the degree of variability in offenses in the observed crime hot spots, the amount of harm contained within those hot spots, and whether crime generators and crime attractors associated with hot spots vary based on the types and severity of the crimes that occur there.

AIMS

This dissertation ultimately has one aim: *to determine if the results in previous crime-related harm spots research are generalizable*. It is well known at this time that unweighted crime follows a specific, non-random geographic distribution and is concentrated in time in very few people and places. Such findings have held in varied settings, but only recently has research begun examining how accounting for harm, or crime severity, affects such spatial and temporal patterns. The present dissertation subscribes to the notion that harm is a missing dimension in the geographic analysis of crime. Acknowledging that the narrow body of existing research has identified different non-random distributions of harm, this dissertation attempts to replicate these findings

through three research studies focusing on: 1) the distribution of harm in space (Study #1); 2) the distribution and clustering of harm in space and time (Study #2); and 3) the identification of unique combinations of facilities and environmental features that are related to “high-harm” and “low-harm” harm spot locations (Study #3).

DATA AND ANALYSIS

The data for the dissertation were obtained from public data portals. Specifically, publicly available geocoded facilities data collected and maintained by referenceUSA were one strand of public data used for the dissertation. The facilities selected for the analysis had been found to be associated with crime hot spots in previous research. These facilities include ATMs, convenience stores, drinking establishments, fast food restaurants, gas stations, lodging locations, liquor stores, banks and other financial institutions, pharmacies, police department locations, schools, and smoke shops. The crime data used for the dissertation was obtained from two separate sources. Specifically, the first set of crime data were obtained from the Open Data Portal for Washington, DC, and include all crimes reported to the police in 2016. The second set of crime data was obtained via an open records request submitted to the Austin (Texas) Police Department and include all calls for service from January 1, 2007 to December 31, 2017. The crime types included in the three studies described below were arson, aggravated assault, burglary, homicide, motor vehicle theft, robbery, sex assault, theft from a motor vehicle, and larceny/theft. These data were geocoded for the purposes of mapping harm spots.

The weights were calculated also using publicly available data/tools, namely the average recommended sentence for UCR Part I Index Crimes from the United States (U.S.) Sentencing Guidelines (United States Sentencing Commission, 2016), Wolfgang, Figlio, Tracy, and Singer's (1985) seriousness scale, and the Cambridge Crime Harm Index developed by Sherman, Neyroud, and Neyroud, (2016).

Descriptive analyses, correlation analyses, and kernel density estimation are used to both validate the American Crime Harm Index and to identify spatial and temporal distributions of harm. Conjunctive analysis of case configurations (CACC) and logistic regression are used to identify unique combinations of facilities that correlate with the presence of harm spots.

RESULTS

In Study #1, the results suggest harm spots are diffused away from the city center into more residential areas. This implies opportunities for more serious offenses could be higher in residential areas, and that different social ecological processes underlie the spatial distribution of more serious crime. This study also supports the continued use of the Cambridge Crime Harm Index based on the U.S. Sentencing Guidelines. Study #2 examined the spatial, temporal, and spatiotemporal distributions of harm. In general, the results were inconsistent with the distributional findings from Study #1, in that harm ultimately follows a different distribution than raw unweighted crime in space. Harm and unweighted crime generally followed major roadways in Austin. When examining the average harm scores for all the data considered at different time periods, the harm scores were highest most often on Sundays, during the winter months, and in the early mornings.

Study #3 examined possible contextual configurations surrounding harm spots using both logistic regression and CACC. The presence of all facilities, without considering the total count of facilities, was significant for all those included in the model, with the exception of law enforcement agencies. Drinking establishment or lodging facility increased the odds of the street segment having a harm score in the top 33% by approximately six and eight times, respectively. When considering the total count of these facilities, the presence of one additional Drinking establishments, hotels and other lodging facilities, and smoke shops increased the likelihood that a street segment was a harm spot by approximately four and five and a half times.

The CACC results indicate that there is evidence that there is an interactive effect that may result in street segments with harm scores in the top 33%; four of the five case configurations with a relative risk difference of 0.70 or greater included more than one facility type. ATMs were present in all configurations; pharmacies were present in all but one. Drinking establishments and financial institutions were only present in one of these case configurations each.

This dissertation contributes to the existing literature examining the clustering of crime in time and space, but while adding the consideration of the disparities in harm between different crime types. The evidence presented indicates that, in order to gain a full understanding of how dangerous an area is, it is important to consider both the raw

crime counts and the weighted harm scores. Considering the relative harm of each offense provides a comprehensive assessment of a hot spot, both in time and space, as it not only considers the number of offenses that occur there, but the type of offense and how objectively dangerous these offenses are. Implications for theory, research, and policy are also detailed.

1. INTRODUCTION

The recent, extensive use of GIS in research and police practice, allows practitioners and researchers to examine questions about spatial criminology in greater detail than they have in the past (Ratcliffe, 2004). In 2002, Ratcliffe argued that "[i]mprovements in geocoding…mean that many crime sites can be mapped, visualized and analyzed with a considerable degree of precision...[allowing] the location of one crime to be scrutinized in relation to the local environment or the relative position of other crime sites" (pp. 23-4). Since then, the field has expanded the use of GIS to improve the understanding of spatial crime patterns, including building tools to better predict where crime may emerge, to decrease the dangerousness of more crime-prone areas.

Most commonly, researchers are familiar with mapping in the form of hot spots analysis, in which GIS programs are used to map the spatial distribution of crime. Such research has been conducted extensively (for example see Braga, 2005; Eck, Chainey, Cameron, Leitner, & Wilson, 2005; Weisburd & Telep, 2014). This extant research has outlined what is known about hot spots and the effects of hot spots policing on crime rates. However, there are still questions that have not been answered, specifically: 1) the degree of variability in offenses in the observed crime hot spots; 2) the amount of harm contained within those hot spots; and 3) whether the location of these spots vary depending on the degree of harm that occurs within them.

Hot spots mapping research originates with Sherman, Gartin, and Buerger's (1989) seminal study where they tested routine activity theory using spatial data. They examined a year's worth of calls for service data from all addresses and intersections in

Minneapolis and discovered that many calls (50%) concentrated in a very few addresses (3%). The authors concluded that crime is both rare and concentrated, resulting in very few "hot spots" of crime. This non-random distribution differs significantly from previous models that estimated random distributions of crime (Sherman et al., 1989; see, for example, stochastic models developed by Avi-Itzahk and Shinnar, 1973), ultimately resulting in a literature dedicated to understanding this non-random distribution of crime. Since this research was published, a number of studies (e.g., Eck et al., 2005; Eck, Clarke, & Guerette, 2007; Weisburd, 2015) have investigated this phenomenon and have arrived at the general conclusion that crime concentrates in space. In addition, this research has also demonstrated that crime concentrates in time and in people, in that the majority of crime takes place at very few places and during specific time periods, as well as concentrating within only a few people, both as offenders and victims.

Despite when or where it occurs, different types of crime differentially affect society, the community, and victims. For example, it is universally accepted that violent crimes are generally more harmful than property crimes, and that crimes that have a significant cost to the victim, such as homicide, are the most serious offenses (Stylianou, 2003). Hot spots that only account for the raw crime volume fail to consider the relative harm that is experienced. This results in an omission of necessary and important information from the calculation of what areas are the most dangerous. Boivin (2014) used this concept to challenge the ranking of the most dangerous cities in Canada, and he revealed that, once you account for the relative harm of the offenses committed in these "dangerous" cities, the list essentially inverted. This was largely due to the fact that many cities with lower crime rates generally had a high harm score, compared to the cities with high crime rates, which seemed to have more crimes with lower relative harm scores. Put simply, two hot spots can appear to be the same on a map based simply on the number of crimes that occur there, but what if one hot spot largely consists of bicycle thefts, and the other largely consists of sexual assaults? It is arguable the second hot spot requires more attention from law enforcement, while the issues at the first hot spot may be solved by adding bike racks for easier storage, or perhaps by implementing a ride-share program. However, both hot spots would be treated equally when based solely on crime volume. By weighting each crime by its relative harm score, maps can be produced that can aid in better targeting problematic points on a map.

Crime can be weighted by its relative severity, or harm, to better display the reality that not all crimes are equal. When these weighted crimes are mapped using a modified kernel density estimation, the points where harm concentrates are known as "harm spots." Presently, very little research has been published on harm spots, despite its growing popularity in criminal justice scholarship.

The existing literature is limited, both in quantity and in its results. Weinborn, Ariel, Sherman, and O'Dwyer (2017) were the first to examine the distribution of harm in space, finding that harm is more clustered than the raw crime counts that are generally examined. Because raw crime is typically used to identify dangerous areas in a jurisdiction, such findings are helpful to law enforcement to narrow resource focus to smaller and fewer geographical areas to increase the impact of these resources on "dangerousness." Norton, Ariel, Weinborn, and O'Dwyer (2018) published a follow-up to this study in which they examined how harm clusters, specifically examining seasonality and temporal trends in harm, and what offenses account for the majority of accumulated harm scores. Other studies have been published developing the Crime Harm Index (CHI), developed by Sherman et al. (2016) for England and Wales (Sherman et al., 2016; Weinborn et al., 2017), New Zealand (Curtis-Ham & Walton, 2017a), and Western Australia (House & Neyroud, 2018).

1.1 The Current Dissertation

This dissertation consists of three studies that intend to build on the existing limited research on crime harm spots to further understand the spatial distribution of harm, the stability of harm spots over time, and their underlying risk factors. The purpose of these studies is ultimately to provide research to inform police practices to better identify and target problematic areas within a jurisdiction.

In this vein, this dissertation will further explore the characteristics of harm by: 1) testing how the distribution of harm differs from the distribution of raw crime volume; 2) determining if previous results are generalizable by replicating past research on harm spots, and expanding these analyses to determine if there are observable patterns of harm clustering in time; and 3) examining the environmental characteristics that are associated with high-harm and low-harm harm spots. Because existing literature on mapping harm is extremely limited and only in its infancy, replication of previous findings is necessary to ensure that the findings from previous research are generalizable. Furthermore, as almost all existing research on harm spots and crime harm mapping has been conducted outside the United States, the studies described in this dissertation serve a broader purpose as well by providing one of the first spatial analyses of harm using data from the United States.

With regard to the theoretical and conceptual framework, the dissertation draws from routine activity theory, crime pattern theory, hot spots mapping, and problem-oriented policing. This theoretical union is designed to better understand the non-random patterns in which crimes occur, and the environmental risk factors that contribute to making a specific location a harm spot versus a hot spot. Such findings have implications for policy regarding focusing on change in policing practices to more efficiently reduce extreme social and physical costs to victims.

The chapters of this dissertation are arranged as follows: Chapter 2 presents the theoretical framework that includes a focus on routine activity theory (Cohen & Felson, 1979) and crime pattern theory (Brantingham & Brantingham, 1984), with a brief discussion of historical perspectives and the theoretical development of environmental criminology. These perspectives are important for each of the three studies described below. Chapter 3 reviews the existing literatures that contribute to the development of the research questions and how they all relate to the present analyses. Specifically, the literature reviewed includes prior research on hot spots mapping, weighting crime by its relative harm, harm spots, and the contextual analyses of hot spots. Such studies have focused investigations into the non-random distribution patterns of crime in space, crime seriousness, crime harm, and environmental and community risk factors.

Chapter 4 is a presentation of Study #1 (Washington, DC data), which involves a comparison of the spatial distribution of raw crime counts and harm-weighted crime counts using three scales: 1) Sherman et al.'s (2016) Crime Harm Index (CHI); 2) a new CHI based on the United States Sentencing Guidelines; and 3) a crime seriousness scale developed from the results of Wolfgang et al.'s (1985) survey. This study also serves as a test for the development of a CHI based on American data.

Chapter 5, Study #2, provides a replication of Study #1 using data from Austin, Texas, and the American CHI scale. This analysis will include spatial, temporal, and spatiotemporal analyses to investigate the clustering and distribution of harm over time and space. Chapter 6, Study #3 (Austin crime data & referenceUSA facilities data), is devoted to an original test of the unique configurations of facilities and other environmental risk factors that are present at high-harm and low-harm harm spots. Study #3 also uses the American CHI to create harm spots. Finally, Chapter 7 provides a summary of the findings, as well as a discussion about the implications for theory, policy, and future research. The chapter ends with overall concluding comments about the findings.

1.2 Data Sources

Geocoded reported offense data are used to measure raw crime counts and to create maps that provide a visual representation of the distributions of both crime counts and crime harm in all three studies. In addition, Chapter 5 includes descriptive analyses to measure the stability of harm spots over time. Chapter 6 also include data obtained from the open-source website referenceUSA and geocoded to match the associated facilities to high-harm and low-harm harm spots.

The data for this dissertation consists of publicly available data from Washington, DC (DC data), Austin, Texas (Austin crime data), and referenceUSA data. The data from Washington, DC were downloaded from the city's open data portal. Many cities are now participating in providing such resources, although larger jurisdictions are generally prone to have more data available than smaller cities and towns. For example, the DC and Austin open portals store hundreds of raw, uncleaned datasets from local government offices and allow the public to access these datasets freely for their own research.

The data from DC includes the address, geographic coordinates, date, and time of every offense reported to the Metropolitan Police Department (MPD) during 2016 (N = 37,183 offenses). The nine crime types included in the study are all UCR Part I Index Crimes, namely arson, assault with a dangerous weapon, burglary, homicide, motor vehicle theft, robbery, sex abuse, theft from an automobile, and other theft. These crimes are defined by the District of Columbia Official Code. The sexual abuse category was reported as such in these data as part of their violent crimes. This is how MPD records forcible rape, and should be considered as such for the purposes of the analysis. In DC, this category includes first and second degree sex abuse, attempted first degree sex abuse, and assault with the intent to commit first degree sex abuse against adults.

UCR crimes typically group theft from an automobile and other theft under the broad category of larcency-theft, but they are grouped separately by the District of Columbia Official Code, resulting in nine crime categories, rather than the eight crime categories that are typically included in Part I Index Crimes. No reason is specifically stated, but it does appear in the Official Code that there is a distinction being made between direct victimization (theft from a person) and indirect victimization (theft from a person's vehicle).

The crime data for Austin were obtained from an open records request. These data include all calls for service for UCR Part I Index Crimes from 2007 to 2017 (N = 145,571 offenses). This sample size changes depending on the analysis and the number of valid cases that are included, and is discussed further in the methodologies for Study #2 and Study #3. These data included the traditional Part I Index Crime categories: arson, aggravated assault, burglary, homicide, larceny-theft, motor vehicle theft, rape, and robbery.

Cases that were labeled family and domestic violence were excluded from the analyses in Study #2 and Study #3. There was no designation for this in the data used in Study #1, and therefore these cases were likely to be included in the analyses. The crimes examined in this dissertation are known as overt crimes (Felson & Eckert, 2018), in which they took place on the street, or in a public place. These crimes are more likely to attract public attention and provide the local population with perceptions of a neighborhood's harm level prior to any empirical investigation (Felson & Eckert, 2018). Family and domestic violence calls are likely to occur behind close doors and go unobserved by the public. Because this dissertation focuses on the amount of harm in an urban area and the effect that it has on the policy and police practices, overt crimes are a better way to explore this.

The data from referenceUSA are similarly publicly available for download. This particular database library focuses on providing up-to-date information on existing businesses in the United States. The facilities data were obtained from this library. These data are geocoded and can be related to crime hot spots and harm spots. A vast array of facilities that are often cited as criminogenic, otherwise known as crime generators and attractors (Brantingham & Brantingham, 1995), have been considered, as Study #3 is largely exploratory. As these data include the most recent facility information, this analysis only includes facilities that were present at the time of downloading these data

(2017). This is a limitation to this analysis and is discussed in greater detail in Section 6.7.

Table 1.1 Descriptions of the three studies including purpose, research questions, site of analysis, and the data sources used.

Study	Purpose	Research Question(s)	Site	Data Source(s)
Study #1	Apply Sherman et al.'s (2016) Crime Harm Index to the United States using the U.K. Sentencing Guidelines, the U.S. Sentencing Guidelines, and harm scores based on Wolfgang et al.'s (1985) crime seriousness survey (NSCS) to understand the spatial distribution of harm in Washington, DC	1) Can the Crime Harm Index be applied to the United States using the U.S. Sentencing Guidelines? 2) How do objective (CHI) and subjective (NSCS) scales compare?	Washington, DC	DC data
Study #2	Replicate and expand previous research examining spatial, temporal, and spatiotemporal stability in harm spots	1) Do the results of the spatial analysis from Study #1 replicate in another urban jurisdiction? Is there an observable spatial pattern to harm? 2) Are harm spots stable in space and over time?	Austin, TX	Austin data
Study #3	Test the unique configurations of facilities and other environmental risk factors present at harm spots	1) Is there a discernable context for high-harm versus low-harm crimes? 1a) Are there unique configurations of facilities/environmental risk factors at harm spots? 1b) Do these configurations differ at high-harm and low-harm harm spots?	Austin, TX	Austin data, referenceUSA data

2. THEORETICAL FRAMEWORK

2.1 Introduction

The present chapter describes the theories providing the framework for the dissertation. Using a framework based on routine activity theory (Cohen & Felson, 1979) and environmental criminology (Brantingham & Brantingham, 1993, 1995), this research ultimately tests the spatial and temporal distribution of harm in urban places. This chapter begins with a discussion of the history of spatial theories of crime, treating them as two discrete historical categories of theories: early 20th century and later 20th century. This includes a description of early theoretical frameworks, such as concentric zone theory and social disorganization theory. The later 20th century theories and research are grounded in a description of routine activity theory and human ecology. This is followed by a description of Brantingham and Brantingham's crime pattern theory. The chapter concludes with the Brantinghams' work on crime generators and attractors.

2.2 A History of Spatial Explorations of Crime

Geospatial theories of crime diverged from traditional paradigms of explaining crime and criminal behavior by specifically examining places as the unit of analysis rather than individuals. Oft-cited criminological theories, including Gottfredson and Hirschi's (1990) self-control theory, Burgess and Akers' (1966) social learning theory, and Hirschi's (1969) social bonds/social control theory, focus on traits of the individual offender. Such traits include: sociodemographic data, such as race, age, and socioeconomic status; psychological traits, such as psychopathy, mental illness, or self-control; or biological traits, such as low birth weight, or inherited traits.

In contrast, the geospatial paradigm of crime and criminal behavior research, more commonly referred to as environmental criminology, does not focus on the on the individual motivations of the offender. Rather, it focuses on explaining criminality given suitable contexts. As such, this theoretical perspective operates under the belief that it is the characteristics of the environment that create unique opportunity structures that are conducive to offending and increase the likelihood that an offense will occur in those locations. Cohen and Felson's (1979) routine activity theory posits that a crime occurs when a motivated offender and a suitable target converge in time and space in the absence of a capable guardian. The offender is assumed to be motivated, therefore, motivation is irrelevant. This idea caused a shift from looking at offenders to looking at offenses.

It is simple to delineate the influence of geography on crime into two different time periods. Classic theory courses in criminal justice often highlight the findings of Park, Burgess, and McKenzie (1925) and Shaw and McKay (1945; Shaw, Zorbaugh, McKay, & Cottrell, 1929) for their contributions to crime research regarding concentric zones and social disorganization, respectively. This comprises the early 20th century theoretical work that informs the dissertation. These early theorists used applications of plant and animal ecology to the study of urban organization and, in turn, described how these organization patterns correlated with delinquency rates of juvenile delinquents. Concentric zones and social organization were early pioneering investigations of *where* crime was clustering, rather than who was committing, or more likely to commit, crime.

This, of course, is a precursor to routine activity theory, in which the theorists outlined the importance of human ecology for understanding why crimes occur where they do. For the purposes of this dissertation, the theoretical work that grew more popular following the publication of routine activity theory is the most important in describing the overarching theoretical framework in the three studies in the dissertation. These theoretical ideas were published in the late 20th century.

2.2.1 Early 20th Century Spatial Tests of Crime

Research examining the environmental influence on crime gained popularity in the latter half of the 20th century, although researchers in the very early years of the 20th century did provide an initial foray into exploring crime with environmental explanations. For example, Robert E. Park, an early ecological scholar partially credited with concentric zone theory, wrote that "[i]t is the social environment to which the person, as distinguished from the individual, responds; and it is these responses…to his environment that eventually define his personality and give to the individual a character which can be described in moral terms" (Park, Burgess, & McKenzie, 1925, p. 100). Park's explanation of the social environment is conceptually similar to the environmental backcloth described by Brantingham and Brantingham (1993) nearly seventy years later, in that the social environment encompasses both individual traits and characteristics as well as the larger social environment. Similarly, Brantingham and Brantingham (1993) indicate that the environmental backcloth includes the individuals and the surrounding environment. However, they also posit there is a psychological component to offense location selection, and therefore describe why an individual is more likely to offend in areas with which they are most familiar. This is described further in Section 2.5.

Pertinent to the dissertation, Park, Burgess, and McKenzie (1925) examined human behavior through the lens of human ecology, specifically focusing on urban environments as the behavioral setting of interest. The authors describe cities as more of an abstract concept (rather than a concrete system) in which the individuals within are the shaping force and the agents of change in the organization. In the constant physical growth of an urban area, known as expansion, Park, Burgess, and McKenzie explain that the organization, disorganization, and reorganization processes that occur during growth result in a patterned and repetitious distribution of individuals and groups within the different zones of a city. This pattern mimics those observed in invasive plant species, and therefore, the tenets of botanical ecology aid in understanding the ecology of urban settings.

Within a city, there are noticeably distinct geographic areas with their own culture that develops from the people that live in these neighborhoods. A neighborhood, by this definition, is "a locality with sentiments, traditions, and a history of its own. Within this neighborhood the continuity of the historical processes is somehow maintained. The past imposes itself on the present…every locality moves on with a certain momentum of its own" (Park, Burgess, & McKenzie, 1925, p. 6). Delinquency is a byproduct of the flux state of urban environments and seems to be localized in neighborhoods that are subjected to high rates of turnover. The transient nature of the population in such neighborhoods is typical of Park, Burgess, and McKenzie's (1925) concentric zone theory. The zone of transition is often characterized by residential deterioration and socially disorganized neighborhoods full of residents that are often only living in this zone because they are attracted to cheap housing and employment. These transition zones often remain criminal, even as the population changes over time, resulting in areas with criminogenic properties where crime often clusters in people, places, and time.

2.2.2 Later 20th Century Spatial Tests of Crime

The geospatial paradigm is rooted in the publication of routine activity theory in 1979 (Cohen & Felson, 1979), and demarcates a starting point for the spatial research of the late 20th century, which has ultimately continued until present. Following this pioneering publication, a significant amount of research began examining crime using the event itself as the unit of analysis and provided a framework on which other significant theoretical works, such as crime pattern theory and the theory of risky places, could build.

Routine activity theory, which is central to each of the three studies, examines crime as a spatiotemporal interaction where motivated offenders and suitable targets converge in the absence of a capable guardian. A more detailed explanation and discussion of the theory is provided in Section 2.4 of this chapter. It is this research that provided a launching platform for the focus in spatial patterns of crime and the analysis of repeat and near-repeat offending. However, because these theories are the most relevant to the dissertation and the three studies, they have been discussed in greater detail below.

2.3 Human Ecology

It is important to also consider the theoretical construct of human ecology. The study of human ecology stems from analogous research on plant and animal ecology, recognizing that the symbiotic relationships in nature mirror the ecological processes in urban areas. Park, Burgess, and McKenzie (1925) defined human ecology as "…the spatial and temporal relations of human beings as affected by the selective, distributive, and accommodative forces of the environment" (pp. 63-4). Park et al. further explain that order and grouping within the population and urban institutions result from the natural existence of forces that act upon them. Human ecology is merely the study of these forces and how they allow a cooperative existence between people and the institutions with which they co-exist (Park, Burgess, & McKenzie, 1925).

It was the work of Hawley (1950) that was most inspirational to routine activity theory, as his work highlighted the temporal component of crime. Routine activity theory states that the three necessary components must meet in space and time in order for a crime to occur (Cohen & Felson, 1979). These theorists also highlight concepts proposed by Hawley that account for the temporal component of criminal opportunity structures and routine activities: 1) rhythm; 2) tempo; and 3) timing. These concepts put into perspective the unique “routine” activities that constitute an individual’s movement throughout the day, on a day-to-day basis, exploring the spatiotemporal patterns of individuals/potential targets with regular frequency and consistency. For example, rhythm may refer to a five-day work week (consistency) and tempo may refer to the twice-a-day commute (frequency) that is required to travel to and from work. Timing is understood to be the interaction of an individual’s rhythm and tempo with another’s rhythm and tempo that put the two into the same place at the same time (spatiotemporal convergence). Timing, specifically, is key to the underlying concept of Cohen and Felson’s (1979) routine activity approach to crime.

2.4 Routine Activity Theory

Cohen and Felson’s routine activity theory was developed in response to a summary report from the National Commission on the Causes and Prevention of Violence in 1969 that indicated that a new social trend had emerged in the Federal

Bureau of Investigation's (FBI) Uniform Crime Reports (UCR). The authors observed a new trend, or "social paradox" (Cohen & Felson, 1979, p. 588). Specifically, while sociodemographic conditions traditionally considered conducive to crime had continued to improve in mid-century America, urban violent crime rates continued to increase significantly.

Cohen and Felson (1979) examined UCR data between 1960 and 1975 and determined that violent crimes such as "robbery, aggravated assault, forcible rape and homicide increased by 263%, 164%, 174%, and 188%, respectively" (p. 588). They argued that the increase in violent crimes was attributable to a major social shift in which individuals were away from their homes more often than they had been prior to World War II. This change in "routine activities," specifically centered on the changing social roles of women during and after World War II, in which more women were entering the labor force while men were deployed, decreasing the amount of time both spent in their homes. This social trend continued, even after male troops returned from overseas.

For purposes of conceptualization, routine activity theory draws from selected concepts from theories of human ecology that explore temporal organization. This relates back to the concept of what the theorists refer to as "routine activities." Routine activity theory focuses on an individual's "routine activities," which are defined as "any recurrent and prevalent activities which provide for basic population and individual needs, whatever their biological or cultural origins" (Cohen & Felson, 1979, p. 593). These activities are the activities in which an individual partakes on a day-to-day basis, such as work or social interactions. Cohen and Felson identify three settings for routine activities: 1) the home; 2) jobs away from home; and 3) any other activities away from home. The theory's basic premise states that crimes are a result of the spatiotemporal convergence in the course of routine activities of three elements, each of which *must* be present in order for a direct-contact predatory crime to occur; the convergence of these three elements is affected by structural changes in patterns of routine activities.

Routine activity theory, therefore, explores the spatial and temporal ordering of crime opportunities and the routines of offenders and victims in order to better understand crime problems. Cohen and Felson focused on the interaction of space and time and how this affects the probability of a direct-contact predatory crime occurring. Research dating back to the early- to mid-nineteenth century supported the idea that crime of place was a valid avenue to pursue, but that this research had rarely considered the interaction of space and time. The theorists also stated that the existing literature had made little headway regarding the influence of social structure on crime rates since Shaw and McKay published their theory of social disorganization.

The three elements that must converge are: 1) a motivated offender; 2) a suitable target or victim; and the 3) absence of a capable guardian to prevent the crime. The absence of any one of these elements is sufficient to prevent a crime from occurring. Cohen and Felson admit that their approach to the explanation of crime excludes an examination of individual or group criminal inclinations as they take this as a given, hence the distinction that a *motivated* offender is necessary for a crime to occur. As such, the source of motivation is unimportant in this context. In fact, Felson and Eckert (2016) indicate that motive, even for specific types of crimes, is as unique as the individual committing the criminal act and imply that motives shift as a potential offender converges with different suitable targets. Instead, the authors focus on how "the spatiotemporal organization of social activities helps people to translate their criminal inclinations into action" (p. 589).

Suitable targets are often those that have some sort of attractiveness to the offender and capable, or effective, guardians are generally marked by the *absence* of crime, which is why Cohen and Felson determined that the guardian role was not often considered in earlier research. It should be noted that Cohen and Felson (1979) imply that the presence of a capable guardian alone is enough to deter crime, but Reynald (2011) discovered that guardians also need to be willing to intervene, not just able to, in order to deter criminal behavior. Put simply, guardians must provide some actual offense-stopping power in order to prevent offending.

The original test of routine activity theory examined the relationship between household activity and index crime rates between 1947 and 1974 (Cohen & Felson, 1979). They used annual time series data for their analysis and highlighted that this only allowed them to examine annual trends. Their own analysis supported the theory of routine activities as the analysis "consistently revealed positive and statistically significant relationships between the household activity ratio and each official crime rate change" (Cohen & Felson, 1979, p. 602) and their model was able to account for up to 77% of the variation in crime changes from year to year. In general, the analysis strongly supported the basic premise of routine activity theory and supported the idea that there is a positive relationship between the amount of time spent away from home and the rate of crime.

Cohen and Felson's (1979) study offers an indication of the predictive utility of routine activity theory. However, identifying research that has specifically tested this theory is seemingly difficult. More often, more recent research uses routine activity theory to help explain the criminogenic properties of place, how or why crime rates vary over time at these places, or to explain the occurrence of specific types of crime. For example, Brantingham and Brantingham (1984) further developed routine activity theory with the introduction of the geometry of crime. They introduced new terms into the criminological lexicon that described how and where routine activities are established: nodes (such as homes, schools, or places of employment), paths (the route between nodes), and edges (the point in which individual "routine boundaries" touch). Brantingham and Brantingham (1984) also explained how the probability of the convergence of the three necessary elements changed in each of these places.

Routine activity theory has also influenced research on crime hot spots. Hot spots were originally discussed by Sherman et al. in 1989. Hot spots by definition are geographic locations that are frequently where a significant number of crimes occur, therefore the routine behaviors of those committing crimes includes frequenting places where targets are readily available and capable guardianship is low. Groff (2007) used agent-based simulation modeling to approximate routine activities to show how routine movement through space and time increased or decreased the probability of street robbery.

2.5 Environmental Criminology

The Brantinghams' work in environmental criminology and the awareness and use of space bears mentioning for a couple of reasons. First, the authors' theory posits that offenders act within their awareness space, which Brantingham and Brantingham have called the "backcloth" (Brantingham & Brantingham, 1993, p. 6), within which offenders often travel between and via well-known nodes, paths, and edges within this space. The environmental backcloth is “the uncountable elements that surround and are part of an individual and that may be influenced by or influence…criminal behavior” (Brantingham & Brantingham, 1993, p. 6).

Offenders acting within their awareness space will likely consider the presence of guardians before they choose to offend within this space. Therefore, if it is known that a specific location is under the watch of any type of guardian, the offender is less likely to offend in that location. They state that “research conducted in either a narrow or broad focus must explore how potential criminals ‘see’ and react to what surrounds them; how they know cognitively what is where; and how they utilize that knowledge (and process for learning what surrounds them) to develop the decision process by which crime choices are made” (Brantingham & Brantingham, 1993, p. 6).

They further explain that the decision to offend is influenced by a complex decision-making process that includes considering the interaction of both motivation *and* the opportunity structure for offending. They suggest that “variation in perceived criminal opportunities influence motivation; motivation influences both the definition of and the search for criminal opportunities” (Brantingham & Brantingham, 1993, p. 4).

Second, the Brantinghams recognize that crime is a complex event with a complex etiology. The presentation of this theoretical perspective offers a cornerstone for a paradigmatic shift in criminology. With the recognition that the etiology of crime is complex and cannot be attributed to a single cause (Brantingham & Brantingham, 1993), the exploration of the environment and its effect on individuals’ behavior becomes incredibly relevant, specifically when considering that a significant amount of literature has identified that behavior is a result of individual differences and the way that these interact with the environment (Brantingham & Brantingham, 1993; for example, Connolly, Lewis, & Boisvert, 2017; Kuo & Sullivan, 2001).

The environmental backcloth is encompassing enough to include what can be conceptualized as structural and natural sources of behavior modification, including the built environment that guides movement between places and the people that exist within those places. This includes both formal and informal social controls, as well as neighborhood characteristics, and therefore includes elements from a wide variety of criminological perspectives.

"Individuals commit crimes for many reasons – ranging from affective motivations such as rage of thrill-seeking to highly instrumental motivations such as greed. Crimes occur in diverse situations under highly varied circumstances. In fact, some researchers are beginning to see motivation and the perception of criminal opportunities as functioning interactively" (Brantingham & Brantingham, 1993, p. 4). In addition, their theory does contend that there is a learning component to offender decision-making, and this learning aspect of environmental criminology includes understanding and learning the routine behaviors of individuals within their environmental backcloth and the scenarios which are best suited for committing a crime.

2.6 Conclusion

This chapter has outlined the central theoretical concepts of routine activity theory, human ecology, and environmental criminology. The dissertation and the three studies contribute to the literature that already exists using this theoretical framework and related concepts, and extends it by investigating further the harm associated with different types of crimes that are committed and the patterns that these crimes exhibit in urban jurisdictions. The following chapter introduces and discusses the existing literature on the distribution of crime in time and space, as well as provides insight into what areas are more conducive to high harm. The research presented here indicates that understanding what makes a place dangerous requires examining more than how much crime occurs, but also how much harm was done by these offenses.

3. LITERATURE REVIEW

3.1 Introduction

The present chapter discusses the existing literature for hot spots and hot spots analysis, crime severity and harm-weighting, and harm spots and harm spot analysis. The dissertation and the three studies are meant to extend spatial analyses of crime on harm spots by marrying hot spots research with research on crime severity, and by weighting crimes by their relative severity. The examination of crime data using these statistical and analytical techniques is by no means a novel approach to crime research. However, weighting each offense by its relative harm permits a unique approach to the crime-related spatial research.

3.2 Hot Spots and Spatial Analysis of Crime

Crime is not randomly distributed in space (Eck et al., 2005; Eck, Clarke, & Guerrette, 2007; Sherman, Gartin, & Buerger, 1989; Weisburd, 2015). Weisburd (2015) has established a law of crime concentration which states, "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd, 2015, p. 138). Often it is clustered at specific addresses, and these clusters are known as "hot spots" (Eck et al., 2005; Sherman et al., 1989). More specifically, a hot spot is commonly defined as an "…area that has a greater than average numbers of criminal or disorder events, or an area where people have a higher than average risk of victimization" (Eck et al., 2005, p. 2). Identifying where crime clusters provides a focused allocation of police resources where they are needed the most (Eck et al., 2005; Eck et al., 2007).

Early literature on hot spots sought to understand how crime was distributed over geographical areas, following the routine activity theoretical framework. For instance, Sherman et al. (1989) determined that 50% of police calls for service were concentrated in 3% of places. To put this into perspective, 323,979 calls for service were recorded over a 12-month period. Half of all calls for police service were clustered at 3% of the estimated 115,000 addresses in the study area. Such clustering of crime is not uncommon, and generally follows the basic premise of the 80-20 rule (or the Pareto law; see Clementi & Gallegati, 2005; see also Eck et al., 2007), in which a large percentage of one thing is concentrated among a small proportion of a group of people or places.

Hot spots analyses focus on the spatial patterning of crime counts. The goal of these analyses is to inform police practices, leading to a more efficient allocation of city and police department resources to areas identified as crime clusters (Eck et al., 2005). This has led to various lines of research including, but not limited to, testing policing techniques to decrease crime at these addresses (for example, Braga, Papachristos, & Hureau, 2014; Braga, Weisburd, Waring, Mazerolle, Spelman, & Gajewski, 1999; Sherman, Buerger, & Gartin, 1989; Taylor, Koper, & Woods, 2011) and determining what environmental factors influence the clustering of crime offenses (e.g., Anyinam, 2015; Drawve, Thomas, & Walker, 2016; Dugato, 2013; Hart & Miethe, 2015; Summers & Caballero, 2017).

3.2.1 Hot Spots Policing Strategy

Hot spots policing strategies have been determined to be effective overall and have been tested in several cities over the course of the past twenty-five years (see Braga & Bond, 2008; Braga, Hureau, & Papachristos, 2011; Braga et al., 1999; Caeti, 1999;

Cohen, Gorr, & Singh, 2003; Lawton, Taylor, & Luongo, 2005; Mazerolle, Price, & Roehl, 2000; Ratcliffe, Taniguchi, Groff, & Wood, 2011; Sherman & Rogan, 1995; Sherman & Weisburd, 1995; Taylor et al., 2011; Weisburd & Green, 1995; Weisburd, Wyckoff, Ready, Eck, Hinkle, & Gajewski, 2006). Questions still remain about the long-term effects and practitioners are left with a significant amount of information that is still currently unknown about this policing strategy (Bayley, 2008; Braga, 2001, 2005; Braga et al., 2014; National Research Council, 2004; Weisburd & Telep, 2014). The National Resource Council (2004) has determined that "focused police resources on crime hot spots [have] provided the strongest collective evidence of police effectiveness that is now available" (p. 250), and Weisburd and Telep (2014) state that "it is no longer enough…to show that hot spots policing works" (p. 202). There now needs to be a focus on the long-term effects, but also what factors are contributing to the eventual return of crime at hot spots that had been the focus of such targeted deterrent strategies.

This cautionary note notwithstanding, in a recent review of this existing hot spots research, Braga and colleagues (2014) reported that research in hot spots policing programs continued to "generate modest crime control gains" (Braga et al., 2014, p. 658). These authors also found support for the diffusion of benefits of crime control into areas surrounding those focused on as hot spots. Furthermore, the results suggested that problem-oriented policing was often the most effective policing strategy in reducing crime (mean effect size = .232, $p < .001$) compared to traditional policing (mean effect size = .113, $p < .001$). Specifically, those "interventions that attempted to alter place characteristics and dynamics" (Braga et al., 2014, p. 658) resulted in the highest percent decrease in crime.

Such hot spot policing strategies focus on decreasing the number of crimes that occur under the assumption that this will make an area safer. However, considering that there are more drastic consequences to violent offending, does decreasing the number of crimes make an area safer? What happens when we take into account the types of crimes and the effect that they have on the victims? This requires creating a scale that can change how much impact an individual offense is having by weighting each offense by its relative harm.

3.3 Crime Severity/Seriousness

Research on crime seriousness originated with Sellin and Wolfgang's (1964) seminal survey that asked respondents to identify which crimes they perceived to be the most serious. Since this research was published, many studies have upheld these results. Crimes that cause the most physical harm (e.g., resulting in bodily injury or death) are consistently rated as the most serious, and violent crimes are consistently rated more serious than property crimes (Adriaenssen, Paoli, Karstedt, Visschers, Greenfield, & Pleysier, 2018; Blum-West, 1985; Stylianou, 2003). This has, therefore, established that there is consistency in public perceptions of crime seriousness. However, consistency does not provide researchers with a quantitative measure to weight crimes by their relative seriousness to weight them for any further research. Researchers recognized this shortcoming, which led them to develop quantitative measures of harm and crime seriousness. More recent research has focused on developing ratio-level scales and indices that indicated the level of harm that different offenses caused (e.g., Ignatans & Pease, 2016; Ratcliffe, 2015; Sherman et al., 2016).

The idea of the additivity of scores was developed to calculate seriousness on compounded offenses (Pease, Ireson, & Thorpe, 1974; Wagner & Pease, 1978). Sellin and Wolfgang's (1964) study represents an original attempt to create an additive scale to measure crime seriousness. However, there was a degree of contention that remained within the literature. For instance, Wagner and Pease (1978) denied that such an assumption was possible and indicated that Sellin and Wolfgang's (1964) best intentions to create a scale of seriousness was not possible. Parton, Hansel, and Stratton (1991) disagreed with Wagner and Pease's (1978) assertion that an additive scale was impossible and indicated that it was simply the methodology used to create it that made it invalid. Despite these disagreements, research attempting to create an additive, ratio-level scale that made crimes quantitatively comparable continued.

Some of these later studies involved applying these scales to crime counts to alter the perceptions of what is considered a dangerous place (Ashby, 2017; Kwan, Ip, & Kwan, 2000; Rossi, Waite, Bose, & Berk, 1974; Sweeten, 2012; Wolfgang et al., 1985). For example, Canada has focused on creating a weighting scale that would allow annual crime reports to consider the dangerousness associated with a crime. Statistics Canada, the agency responsible for publishing information on crime rates in Canada, has previously reported crimes based on reported crime and victimization surveys, but both perspectives led to reporting crimes as if all crimes are generally equal (Babyak, Alavi, Collins, Halladay, & Tapper, 2009). They have since developed a new perspective of crime reporting using a third measure they have developed in-house called the Police-Reported Crime Severity Index (PRCSI) with the goal of addressing the belief that not all crimes should be counted equally (Babyak et al., 2009; Sherman et al., 2016).

3.3.1 Crime Harm Index and Harm spots

With a focus on harm-focused policing in the literature, the opportunity to explore and develop methods of spatial analysis to identify where harm generally concentrates does exist (Curtis-Ham & Walton, 2017b). Sherman et al. (2016) explicitly stated that not all crimes are created equal, essentially summarizing the need for considering harm and dangerousness *in addition to* raw crime counts to determine how dangerous an area may be. Relatedly, Boivin (2014) considered how much harm was caused to identify which city in Canada was truly the most dangerous. This helped show how this additional dimension of harm affects the crime outcomes at a higher level of aggregation. Boivin (2014) argued that cities with high crime counts may not necessarily be the most "dangerous." Rather, dangerousness depends on the *type* of offenses that occurred there.

In contrast, in the United Kingdom (Sherman et al., 2016) and in New Zealand (Curtis-Ham & Walton, 2017a, 2017b) harm indices have been developed using sentencing guidelines. Weinborn et al. (2017) generated harm spots based on the recommended construction of a universal harm index developed by Sherman, Neyroud, and Neyroud (2016). In general, Sherman et al.'s (2016) publication serves as a guide for constructing a Crime Harm Index (Cambridge CHI) using official data from any country. The original CHI is based on sentences from the U.K. Sentencing Guidelines and considers every offense at a baseline level, following the suggestion that, regardless of the offender's record, a homicide results in the same harm to the victim/s. Curtis-Ham and Walton (2017b) conducted a similar study based on Sherman et al.'s (2016) CHI in New Zealand.

Other approaches to creating such an index have previously constructed harm indices based on actual sentences and criminal histories (see Babyak et al., 2009; Francis, Soothill, Humphreys, & Bezzina, 2005; Sullivan & Su-Wuen, 2012), under the presumption that this reflects popular opinion. But considering actual sentences assumes the inclusion of additional unnecessary variables versus a simple consideration of the harm caused to the victim (Sherman et al., 2016; Sullivan & Su-Wuen, 2012; Sullivan, Su-Wuen, & McRae, 2017). Other techniques have included crime victim scores (see Ignatans & Pease, 2016) and sentencing gravity scores (see Ratcliffe, 2015). Crime victim scores are calculated based on the victims' assessments of how serious the offenses committed against them were. Ignatans and Pease (2016) collected this data and developed this scale using the Crime Survey for England and Wales. Sentencing gravity scores resulted from a non-mandatory scoring system developed by the Pennsylvania Sentencing Commission to assist judges in determining the appropriate punishment for an offense. This scale ranges from 1 to 15, and is a truncated version of the scoring system that was developed for the Federal Sentencing Guidelines.

The problem with using crime victim scores is that they are often lacking for rare crimes, or for crime types where victims are unable to score the offense (e.g., in the case of homicide), and Ratcliffe's (2015) sentencing gravity scores is based on a 15-point scale and may not completely reflect the total harm caused to the victims or society. While there are a number of available options for weighting crime by its relative harm, the dissertation and the three studies utilize the CHI developed in Cambridge by Sherman and his colleagues (2016). This is because this scale has been used in spatial analyses of harm in previous research (Curtis-Ham & Walton, 2017a, 2017b; Norton et al., 2018;

Weinborn et al., 2017). Regardless of how crime is weighted, these scales can be applied in crime analyses to understand how harm clusters in space and time.

There are three requirements that must be met for the construction of a crime harm index. It should be democratic (reflect the will of the people), reliable (can be consistently applied), and be cost-effective for the agencies implementing it. The use of the U.S. Sentencing Guidelines to construct a weighting scale passes this three-pronged test (Sherman et al., 2016) and it “offers the lowest cost and [the] greatest speed. It is readily available to be applied to any set of crimes” (p. 177). The weights can then be constructed using the recommended sentences based on the sentencing table.

The U.S. Sentencing Guidelines were developed, written, and maintained by the U.S. Sentencing Commission, which was established as a result of the Sentencing Reform Act of 1984. The purpose of the Sentencing Commission is to ensure that recommended sentences are appropriate for the crimes that are being committed. There are seven voting members of the commission, each of which are selected by Presidential appointment and confirmed by the Senate. The Commission members are advised by four advisory groups (Practitioners Advisory Group, Probation Officers Advisory Group, Tribal Issues Advisory Group, and Victims Advisory Group). The work of the Sentencing Commission is meant to ensure that sentencing is a consistent practice when the Guidelines are utilized, and the public availability through the Sentencing Commission’s website ensures that the U.S. Sentencing Guidelines are free to use for any person wishing to utilize these sentencing recommendations to develop a crime harm index.

3.4 Harm Clustering

It is known that crime clusters in space and time, to the point that these patterns have become predictable and are often used in proactive/problem oriented policing strategies in order to prevent future offending in those areas that are prone to such clustering (Weisburd & Eck, 2004). Such questions are still pertinent when examining how weighting each offense by its relative harm changes these findings. Weinborn et al. (2017) have examined the spatial clustering of harm, and Norton et al. (2018) reported the temporal clustering of harm. No other research has been published, to date, examining crime harm clustering.

Before continuing, a discussion of what harm is for the purposes of this dissertation is required. In the literature, the conceptualization of harm, as it exists in the present document, has been used interchangeably with severity and seriousness. As such, one should assume that the term "harm" in this dissertation is to mean *how serious, or costly, an offense is to the victim.* This means that when one offense is compared to another, the one that is deemed "more harmful" will generally be considered to have a greater impact on the victim. In other words, in a theft, a victim may lose belongings, but remain otherwise unharmed. In a sexual assault, a victim may suffer more serious bodily and emotional injuries with longer lasting effect. As such, the argument could be made that a theft is much less *harmful* than a sexual assault.

Currently, the findings are mixed regarding the degree of spatial clustering of harm. For example, Weinborn et al. (2017) found that, while 50% of all crime clustered at approximately 3% of the addresses in their sample, 50% harm clustered at fewer than 1% of the addresses in the sample. This study was subject to the same problem that

Boivin (2014) attempted to address in his study, in that the use of raw crime, without controlling for the raw counts of different offenses, prevents a true assessment of harm-weighted crime from being estimated. Comparatively, Norton et al. (2018) report that the spatial distribution of harm is not uniform. Having said this, Norton et al. (2018) also demonstrated that the spatial distribution of more serious offenses was more random. However, they did note that harm did accumulate with volume.

Predictably, Norton et al. (2018) reported that harm is concentrated in very few crime offense categories, such that 80% of the total harm in their sample was concentrated in four offense categories, namely sexual offenses, violence against persons, robbery, and theft. Theft was determined to be the most numerous offense category. These findings continue to raise the issue with the effect of pure volume on crime perceptions and perhaps question the implications of the inflated belief that individuals are at a higher risk of personal victimization or serious injury than what the existing data may imply. High-volume crimes often result in areas continuing to be identified as a harm spot (Norton et al., 2018) simply due to the accumulation of harm, not because the crimes that are being committed in those areas are truly harmful, as would be the case in more serious offenses like homicide or sexual assault (Stylianou, 2003). High-volume crimes are more indicative of a higher risk of victimization, which is likely conflated with high risk of personal harm, given findings in the fear of crime literature. Objectively, these high-volume crimes are much less harmful than crimes that are more rare.

Finally, Norton et al. (2018) found that harm is concentrated in night-time and weekend offending, and a trajectory analysis showed that harm spots revealed evidence of long-term stability and that these spots often remained chronically affected by higher levels of harm. To date, there are no other studies that have examined the temporal distribution and clustering of harm, so the generalizability of these findings is still an empirical question. For this reason, Study #2 in this dissertation replicates and expands on previous research examining the spatial and temporal clustering of harm to determine if these results are generalizable.

3.5 Conclusion

While a significant amount of research has been dedicated to hot spots mapping and analysis and to crime seriousness, only recently have these two disparate literatures been examined together. Harm spot mapping and analysis have only recently gained attention in the criminological literature, and therefore important empirical questions remain unanswered. For example, is there a discernable pattern of harm in time and space, and are there any risk factors that can be identified empirically that contribute to the harm score at a given location?

The following three chapters of the dissertation present the three studies that aim to begin to address the new research questions that have been created from joining the research literatures on hot spots mapping and crime seriousness, specifically focusing on exploratory research meant to identify trends in spatial and temporal clustering, and the environmental context of harm spots. Study #1 explores the use of the CHI in the United States (DC data) relying on one year of official data and compares different weighting scales. Study #2 is meant to attempt to replicate Study #1's results with more data (ten years' worth of calls for service) and in a different jurisdiction (Austin data).

Study #3 (Austin data and referenceUSA data) examines the environmental context of harm spots. This is largely exploratory, although it is expected that the "usual suspects" are likely to be present at street segments with significantly greater than average harm. It is typical that areas of mass transit are often areas where more crime is prevalent. It is expected that facilities that often draw a significant amount of foot traffic, such as bus stops (Loukaitou-Sideris, Liggett, & Iseki, 2001) and entertainment venues (e.g., casinos, see Barthe & Stitt, 2007), are likely to have greater than average harm. The dissertation and these three studies can contribute to the growing body of literature investigating harm spots by identifying if there is a noticeable and repeating trend in the spatial and temporal distributions of harm.

4. MAPPING HARM SPOTS: A COMPARISON OF CRIME SERIOUSNESS WEIGHTING SCALES[1]

4.1 Abstract

Recent attention to the use of harm indices to weight crime counts in mapping analysis has led to the development of "harm spot" maps. Early studies have shown that harm spots (i.e., clusters of harm-weighted crimes) follow geographic patterns similar to (unweighted crime) hot spots, although harm spots have been found to be even more spatially concentrated than hot spots (Weinborn et al., 2017). Study #1 explores whether the spatial distribution of harm spots using police-recorded crime data for Washington, DC, differs when different weighting indices are used. The results suggest the level of geographic concentration remains fairly stable across the three harm-weighted distributions and the unweighted crime distributions. However, harm spots are diffused away from the city center into more residential areas. This implies opportunities for more serious offenses could be higher in residential areas, and that different social ecological processes may underlie the spatial distribution of more – versus less – serious crime.

[1] The material from this chapter contributed significantly to a manuscript submitted and published in *Applied Geography.* The reviewed and edited manuscript has since been published. The citation for the publication is as follows: Fenimore, D. M. (2019). Mapping harmspots: An exploration of the spatial distribution of crime harm. *Applied Geography, 109,* 102034.

4.2 Introduction

It is commonplace for researchers and others to rank cities, neighborhoods, states, and even countries as safe or risky places based on crime counts or annual crime rates. These ranks tend to be based on violent crime or even all crime (of any type), without considering the amount of harm that is caused by each specific type of crime, which can make such rankings misleading. For example, a list of Canada's most dangerous cities identified Prince George as high-risk, despite most of the crime there consisting of thefts and other lesser crimes. In contrast, a very different list resulted when the seriousness of the crimes were taken into account (ranks were calculated as the ratio between the crime-seriousness-weighted and unweighted crime counts; Boivin, 2014). Specifically, Toronto went up from 75th (out of 104 cities) to the 2nd most dangerous city, Montreal from 45th to 3rd, and Calgary from 62nd to 9th. From such findings, Boivin (2014) concluded that "…crime rates, considered only as volume of crime, fail to reflect the intensity of crimes in a society…" (Boivin, 2014, p. 905).

The idea that crime should be weighted based on seriousness to fully understand the effect it has on communities has been recently applied to hot spots maps, which tend to consider crime patterns at a micro level. One of the very few studies in this area have shown that harm is more spatially concentrated than raw crime counts (Weinborn et al., 2017). To date, however, there has been no systematic comparison of crime harm/seriousness weighting scales, and how their use can affect the resulting harm spot maps. This research aims to contribute to the evidence base by answering this very question, using crime data from Washington, DC, and weighting methods proposed by Sherman et al. (2016) and Wolfgang et al. (1985). Study #1 is structured as follows: first, the existing literature is reviewed, discussing the development of harm spot mapping. The focus is on spatial crime analysis, the analysis of geographic hot spots of crime, and the creation of crime seriousness scales. The review of the literature concludes with a summary of research conducted specifically on mapping harm spots. The data sources and analytical strategy are then described, and this is followed by a discussion of the results of these analyses. Study #1 ends with a discussion of the findings, including the theoretical and policy implications of examining the spatial patterning of crime severity.

4.3 Literature Review

4.3.1 Spatial Analysis of Crime

It is generally agreed upon that crime is not randomly distributed in space (Eck et al., 2005; Eck et al., 2007; Sherman, Gartin, & Buerger, 1989; Weisburd, 2015). Weisburd (2015) has formalized a law of crime concentration, which states, "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd, 2015, p. 138). Research supports such a law. For example, Sherman et al. (1989) found that 50% of 323,979 police calls for service in Minneapolis over a 12-month period were concentrated in 3% of places. Such clustering of crime is not uncommon, and generally follows the basic premise of the 80-20 rule, also known as the Pareto law (see Clementi & Gallegati, 2005; Eck et al., 2007), in which a large proportion (about 80%) of cases relates to just a small proportion (20%) of units.

When crime is clustered at specific addresses or other small places, these clusters are referred to as "hot spots" (Eck et al., 2005; Sherman et al., 1989). More specifically, a hot spot is commonly defined as an "…area that has a greater than average numbers of criminal or disorder events, or an area where people have a higher than average risk of victimization" (Eck et al., 2005, p. 2). As the geographic unit becomes smaller, crime becomes more concentrated. The goal of hot spot analysis has generally been to inform police practice so that limited resources can be efficiently and effectively allocated (Eck et al., 2005; Eck et al., 2007). This has led to various lines of research including, but not limited to, testing policing techniques to decrease crime at these addresses (see Braga & Bond, 2008; Braga, Hureau, & Papachristos, 2011; Braga et al., 1999; Caeti, 1999; Cohen, Gorr, & Singh, 2003; Lawton et al., 2005; Mazerolle et al., 2000; Ratcliffe et al., 2011; Sherman, Buerger, & Gartin, 1989; Sherman & Weisburd, 1995; Taylor et al., 2011; Weisburd & Green, 1995; Weisburd et al., 2006), determining what environmental factors lead to the clustering of crime offenses at one address (e.g., Anyinam, 2015; Drawve, Thomas, & Walker, 2016; Dugato, 2013; Hart & Miethe, 2015; Summers & Caballero, 2017), and identifying targeted programs and policies that prevent offending or can mitigate the effects of it (Braga, 2001, 2005; Braga, Papachristos, & Hureau, 2014; Chamlin & Scott, 2014; Koper, Taylor, & Woods, 2013; Lum, Hibdon, Cave, Koper, & Merola, 2011; National Resource Council, 2004).

The concentration of crime at specific addresses also helps to identify which areas are the most dangerous and has implications for community and neighborhood levels of fear of crime (Wyant, 2008). Crime seriousness scales can be useful in refining the dangerousness approximations provided by hot spots maps and allow for alternative insights on what is a dangerous place (Ashby, 2017; Kwan et al., 2000; Rossi et al., 1974; Sweeten, 2012; Wolfgang et al., 1985).

4.3.2 Measuring Crime Harm

Crimes that cause the most physical harm (e.g., resulting in serious bodily injury or death) are consistently rated as the most serious, and violent crimes are consistently rated more serious than property crimes (Adriaenssen et al., 2018; Blum-West, 1985; Stylianou, 2003). Crime harm has been estimated using both subjective and objective approaches. Subjective approaches are generally based on public perceptions, while objective approaches use official statistics, such as sentence lengths or social costs, to weight crimes. Research on weighting crimes and how these can provide more accurate measures of dangerousness have been conducted primarily in Canada (Babyak et al., 2009; Boivin, 2014) and the United Kingdom (Ariel, Weinborn, & Sherman, 2016; Weinborn et al., 2017), with some studies also emerging in China (Kwan et al., 2000), New Zealand (Curtis-Ham & Walton, 2017a), Western Australia (House & Neyroud, 2018), and select locations in the United States (Burton, Finn, Livingston, Scully, Bales, & Padgett, 2004; Ratcliffe & Kikuchi, 2019).

The first notable attempt to develop a crime seriousness scale and produce a viable way to weight offenses dates back to Wolfgang et al.'s (1985) seminal survey of public perceptions, known as the National Survey of Crime Severity (NSCS). This scale was created by asking 60,000 respondents to rate the seriousness of hypothetical crime-related scenarios, each time comparing these to bicycle theft, which the researchers assign a seriousness score of 10 and used as a point of reference. For instance, an offense given a score of 20 would be perceived as twice as serious as a bicycle theft. The crime seriousness score for each offense type was calculated as the geometric mean of all respondent scores for that particular offense. An adapted version of the NSCS, in which the media scores of similarly categorized offense-scenarios are used to weight the recorded offenses, is one of the three weighting scales considered in this study.

Other studies employing subjective measures have involved seeking ratings from crime victims (e.g., Ignatans & Pease, 2016), although these are often unreliable for rare crimes and lacking when victims are unable to score the offense (e.g., in the case of homicide). No formal crime seriousness scales have been developed based on this type of data.

Objective approaches to the measurement of crime seriousness have aimed to assess crime harm via sentence severity and/or official crime statistics. For example, Statistics Canada, the agency responsible for publishing information on crime rates in Canada, calculates a crime severity score as the annual average of the sentences given for each crime type multiplied by the relevant observed incarceration rate. The Police-Reported Crime Severity Index (PRCSI) can then be derived by calculating the crime severity score for the last five years. This index is updated every year and used to calculate harm-weighted annual crime rates (Babyak et al., 2009). Although harm indices based on actual sentences and criminal histories have been argued to be a good proxy for popular opinion, sentences received are also influenced by variables unrelated to the harm caused to the victim, such as the offender's criminal history and aggravating and mitigating circumstances of the offense (e.g., submitting pleas of diminished capacity, or insanity, in objectively serious cases to reduce the charge or sentence; see Sherman et al., 2016; Sullivan & Su-Wuen, 2012; Sullivan et al., 2017).

To overcome this issue, some authors have developed harm scales based on sentencing guidelines (rather than the sentences actually given; e.g., Curtis-Ham &

Walton, 2017a, 2017b; Ratcliffe, 2015a; Sherman et al., 2016). Sherman et al.'s (2016) Cambridge Crime Harm Index (CHI) is based on U.K. Sentencing Guidelines, more specifically the baseline or "starting point" level for sentences. This approach, they argued, is more appropriate in that the harm resulting from a crime is not affected by the offender's record, whereas the actual sentences received can be. Sherman et al. (2016) favored the starting point over the maximum sentences, as the latter are less likely to capture a "typical" sentence for a particular crime. Mid-range/median tariffs are also stipulated in the U.K. Sentencing Guidelines, but these are calculated after taking into consideration aggravating and mitigating factors and are, therefore, less suitable. In their view, using the starting point approach "would reflect the nature of the offense, rather than the offender, and would allow a substantial differentiation between…a murder and a bicycle theft" (Sherman et al., 2016, p. 177).

The CHI is based on the number of days of imprisonment. Where offenses require that the offender pay a fine instead, the sentences are converted to prison days by calculating how many days it would take to pay the fine at minimum wage pay. Community service sentences are similarly converted into days. The purpose of Sherman et al.'s (2016) study was to provide a guide for applying a general crime harm index to any country's official data. To date, Sherman et al.'s (2016) Cambridge CHI has only been adapted for use in New Zealand (Curtis-Ham & Walton, 2017b).

4.3.3 Harm Spots Mapping

Recently the concept of considering crime seriousness when studying crime patterns has been applied to crime mapping and led to the development of harm spot maps (Weinborn et al., 2017). Heat maps, or hot spots analyses, focus on the density of raw crime counts and, as such, can fail to emphasize how dangerous a specific area may be, simply because they treat all crimes equally. But, as argued, different types of crime have different levels of potential harm. Harm spot maps aim to address this issue by applying a relative weight to each incident when examining where crime clusters geographically. The goal here is to provide a more thorough definition of what areas are "high" and "low" in crime, after having considered the potential harm to the surrounding community.

Harm spot analysis is relatively new, with only one study having been published to date applying this analytical strategy. Weinborn et al. (2017) generated harm spots using Sherman et al.'s (2016) CHI to weight crime incidents. The results of this analysis indicated that harm-weighted crime is more concentrated than raw crime counts. The authors found that 50% of crime events were concentrated in 3% of all street segments, while 50% of harm was concentrated in only 1% of street segments. The results of this research indicated harm is even more likely to adhere to Weisburd's (2015) "law of concentration of crime in place." Weinborn et al. (2017) argued that focusing on harm increases cost-effectiveness of police patrol and reduces the risk of crimes that are more likely to cause significant harm to victims.

4.4 The Current Study

Weighting a crime by the gravity of its effects provides a better measure of how dangerous a place can be (Boivin, 2014). However, there is no consensus yet as to which weighting system should be used in ranking tables and/or harm spot maps. The harm spot map literature is also extremely limited, and more research is needed to validate any emerging findings. To address these issues, Study #1 explores how the level of spatial concentration and the distribution of risk varies across (unweighted) crime hot spots and (harm-weighted) harm spot maps, using three different crime seriousness weighting scales to weight all Part I Index Crimes in DC reported in 2016

4.5 Methods

4.5.1 Data Sources

Geocoded crime data recorded in the District of Columbia (DC) area are used in the present study. These data include the address, geographic coordinates, date, and time of every offense reported to the Metropolitan Police Department during 2016 (N=37,183 offenses). It must be kept in mind these data *only* include reported crimes in Washington, DC, and that the city expands beyond the District's official boundaries. Unfortunately, data for the counties bordering DC are not available and cannot be incorporated into the analysis. This will lead to boundary effects (i.e., inaccurate density estimates near the boundaries).

The crime data were downloaded from Washington, DC's open data portal (http://opendata.dc.gov/), which stores thousands of raw, uncleaned datasets from all offices in the local government for the public to access freely for their own research. The nine crime types included in the study are all UCR Part I Index crimes, namely arson, assault with a dangerous weapon, burglary, homicide, motor vehicle theft, robbery, sex abuse, theft from an automobile, and other theft. Assaults with a dangerous weapon were disaggregated into two offense types, based on a secondary variable (method) that indicated the type of weapon used; the two new offense types were assaults with guns and/or knives, and assaults involving other weapons. The former were categorized as "aggravated assaults," and the latter as "other assaults." This resulted in 10 crime categories that better matched the offenses used by Sherman et al. (2016). These categories, with their corresponding number of recorded crimes, are listed in Table 4.1.

Table 4.1 Number and percentage of offenses in 2016 in Washington, DC, and corresponding raw and standardized crime weights for each of the three crime seriousness scales, by crime type.

	Recorded crime		CHI_{UK} scores		CHI_{US} scores[a]		NSCS scores[b]	
	N	%	Raw	Std.	Raw	Std.	Raw	Std.
Property Offenses								
Arson	6	<0.03	33	0.6	810	22.3	22	56.4
Burglary	2,121	5.7	20	0.4	540	14.9	6	15.4
Motor vehicle theft	2,690	7.2	20	0.4	810	22.3	8	20.5
Other theft	14,511	39.0	2	0.0	0	0.0	3	7.7
Theft from auto	12,135	32.6	2	0.0	0	0.0	7	17.9
Violent Offenses								
Aggravated assault	1,580	4.3	20	0.4	450	12.4	16	41.0
Homicide	136	0.4	5,475	100.0	1,890	52.1	39	100.0
Other assault	689	1.9	1	0.0	0	0.0	7	17.9
Robbery	2,969	8.0	365	6.7	990	27.3	9	23.1
Sexual abuse	346	0.9	365	6.7	3,630	100.0	20	51.3
Total	37,183	100.0						

[a] Scores were calculated using the U.S. Sentencing Guidelines (see Appendix 1).
[b] Scores were calculated using the National Survey of Crime Severity (NSCS) scores by Wolfgang et al. (1985; see Appendix 2).

4.5.2 Crime harm weighting scales

Three separate weighting scales were compared for this study. The first was developed by Sherman et al. (2016) using the U.K. Sentencing Guidelines. This scale was published as the Cambridge Crime Harm Index (CHI; CHI_{UK} for the purposes of Study #1). The second scale follows the guidelines provided by Sherman et al. (2016) for creating a CHI, but uses the U.S. Sentencing Guidelines to calculate the weights (CHI_{US}, hereafter); the specific offenses (as recorded in the sentencing guidelines) considered for each of the 10 categories in this research are listed in Appendix 1. Finally, the third scale was adapted using median scores of offenses listed in the NSCS by Wolfgang et al. (1985; rounded to the nearest whole number, to be consistent with both CHI scales; see Appendix 2). Once all three scales had been finalized, they were standardized to a 0-100 proportional scale to make them comparable. It is these transformed scales that were then used to create the harm-weighted kernel density estimation (KDE) maps. The weights assigned to each of the 10 offense types in this scale are displayed in Table 4.1.

4.6 Results

A cursory visual examination of the unweighted spatial crime distribution (see KDE map in Figure 4.1, map A) shows that crime clusters in the city center. This is where most of the entertainment venues and tourist attractions are located, and such patterns are consistent with prior research (e.g., Bernasco & Block, 2011; Brantingham & Brantingham, 1995; Kinney, Brantingham, Wushke, Kirk, & Brantingham, 2008); several universities are also located close to this area. Maps B, C, and D account for weighted crime counts in which darker spots no longer are indicative of where more crimes have occurred, but rather the density of harm. Figures B and C both show that harm is less dense in the center of the city. The density map still indicates the city center to be a notable harm spot, although this is due to the accumulation of low-scoring crime counts that mimic more serious offending patterns that are observed further from the city center.

There are two observations that can be made once the CHI scales are considered in the kernel density estimation. First, reported offenses are no longer as centrally concentrated, as they are in map A, and are more evenly distributed throughout the district. Concentrated areas also seem to have dispersed from the city center. In other words, harm density appears to be more randomly distributed than the raw crime counts in Maps B and C in Figure 4.1. Indeed, harm may be the result of a different, non-random process than the non-random distribution of crime in general.

Second, there are “harm spots” where offenses associated with higher levels of harm can undoubtedly be observed (when the distribution of each offense type is examined independently of the other types). It should be further mentioned that the darkest concentrated areas are not in the same part of the District where raw counts were generally clustered; rather it is much further south, which looked like a lower crime area when treating all crimes as equal.

Harm-weighted crime also generally concentrates in the city center (maps B, C, and D), and this is due to the pure volume of lesser crimes in the area. Furthermore, the stability of the city center hot spot across the different maps illustrates how the combined total harm of lesser crimes can keep the area hot because of the frequency with which they occur. More serious offenses occur much less often, but because they are weighted much more heavily in the harm spot maps they lead to the emergence of additional hot spots away from the city center. This was the case for the CHI-weighted harm spot maps, in particular the U.K. version. Surprisingly, the NSCS-weighted harm spot map lacked such additional hot spots, but harm does appear to be more dispersed than the unweighted KDE map. This is much more emphasized in map B and map C, which were created with the CHI-weighted data.

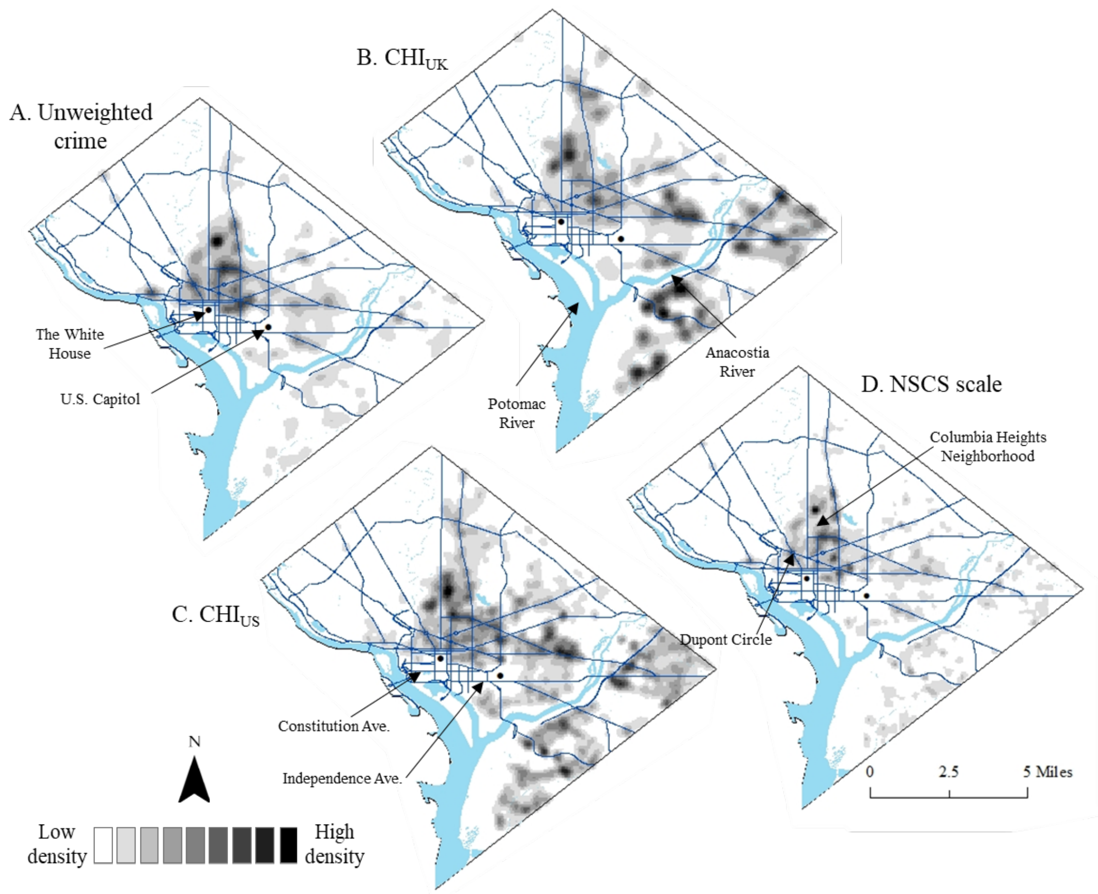


Figure 4.1 Kernel density estimation (KDE) maps of all crime, based on unweighted crimes (map A), and crimes weighted using the U.K. version of the Crime Harm Index (CHIUK; map B), the U.S. version of the CHI (CHIUS; map C), and the National Survey of Crime Severity (NSCS) scale.

The empirical cumulative distribution function (ECDF) in Figure 4.2 (which uses the cells in the KDE map grid as the unit of analysis) indicated 80% of all crime occurred within approximately 18% of the total number of cells. This level of crime density is consistent with previous research (Eck et al., 2005; Eck, Clarke, & Guerette, 2007; Sherman, Gartin, Buerger, 1989; Weisburd, 2015). The ECDF also indicates 100% of crime occurs within about 45% of all cells. When using the CHI_{UK}-weighted scale, 80% of the total harm is contained within approximately 16% of all cells. Similarly, when the CHI_{US} and the NSCS scales are applied, 80% of all harm occurs within approximately 19% of all cells. The weighted and unweighted crime maps are extremely similar, and likely within the range of expected variation. This is consistent with the findings of Weinborn et al.'s (2017) study, where harm was found to be nearly equally concentrated as unweighted crime (50% of harm contained within 1% vs. 50% of crime contained within 3% of street segments). The differences in the percentage of concentration is likely related to different units of analysis being examined between the two studies. The present study considers concentration of the number of grid cells from a KDE map, while Weinborn et al. (2017) examined street segments.

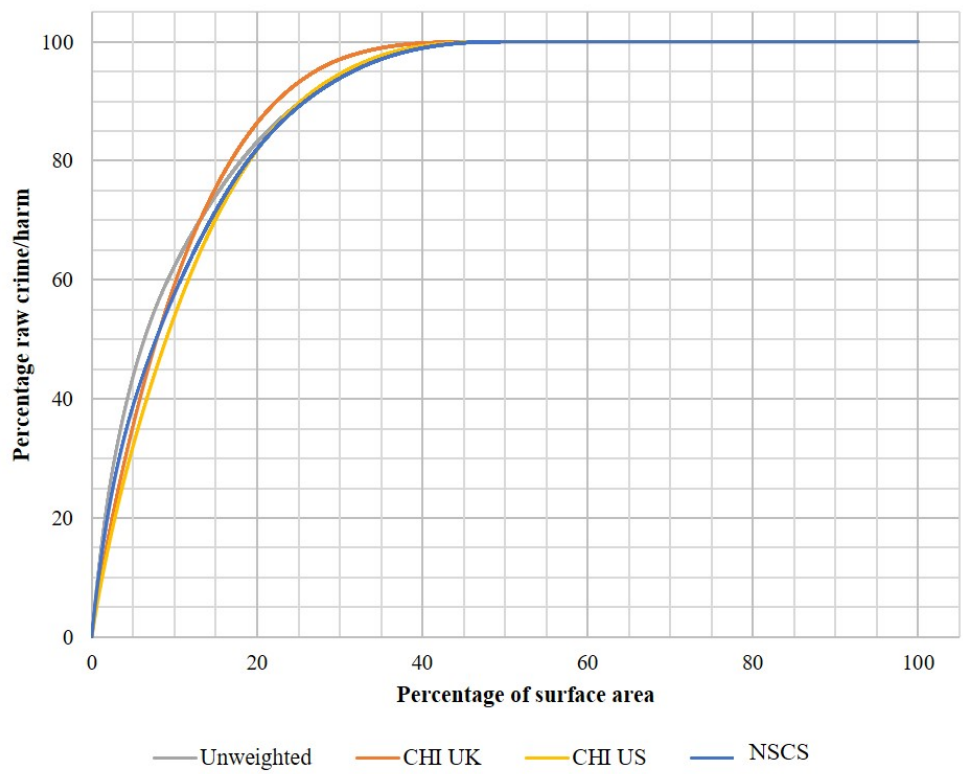


Figure 4.2 Spatial concentration of unweighted and harm-weighted crime, using the kernel density estimation (KDE) cell as the unit of analysis, and the Crime Harm Indices (both U.K. and U.S. versions), and the National Survey of Crime Severity (NSCS) scale.

Correlation analyses also using the KDE map grid cell as the unit of analysis revealed strong correlations among all maps, with the highest coefficient (r=0.99) being that for the association between the unweighted crime hot spots and the NSCS-weighted harm spot maps (see Table 4.2). The correlation between the two CHI-weighted harm spot maps is positive and strong (r=0.94), which is to be expected considering both scales are constructed using the same methodology. All correlations were significant at the 0.001 level, which is not surprising given the sample size (N=71,535 cells).

Table 4.2 Bivariate correlations between the kernel density estimation (KDE) cell values from the unweighted crime and the harm- weighted crime distributions, based on the Crime Harm Indices (CHI), U.K. and US versions, and the National Survey of Crime Severity (NSCS) scale.

	A	B	C
A. Unweighted			
B. CHI_{UK}	0.75		
C. CHI_{US}	0.87	0.94	
D. NSCS	0.99	0.81	0.92

N.B.: All results are significant at the p<.001 level (N= 71,535 cells).

The concentration of harm displayed in Figure 4.2 is present is despite there not being enough crimes to fill each raster cells in each of the KDE maps. As such, this results in a systematic increase in the number of zeros in the data. This also results in an artificial inflation of the effect sizes, which can be observed in the abnormally large correlation coefficients in Table 4.2. These values are mentioned to compare and contrast the use of each scale, but some of the results should be interpreted with this as a caution.

Taken together, these results indicate that harm density appears to follow a slightly different geographic pattern than unweighted crime, despite harm being similarly concentrated. In the three harm spot maps, the higher-intensity (darker) spots no longer are indicative of where *more* crimes have occurred, but rather where *the most harmful* crimes, and more specifically homicides, are located. The concentration of harm close to the southeast border of the District is more evident as well. Thus, it is arguable that the southeastern part of the District is equally as “harmful” as the city center – at least when harm is estimated using the CHI scales – but has a lower crime rate overall. Harm may be the result of a different, non-random process than the one underlying the development of crime hot spots.

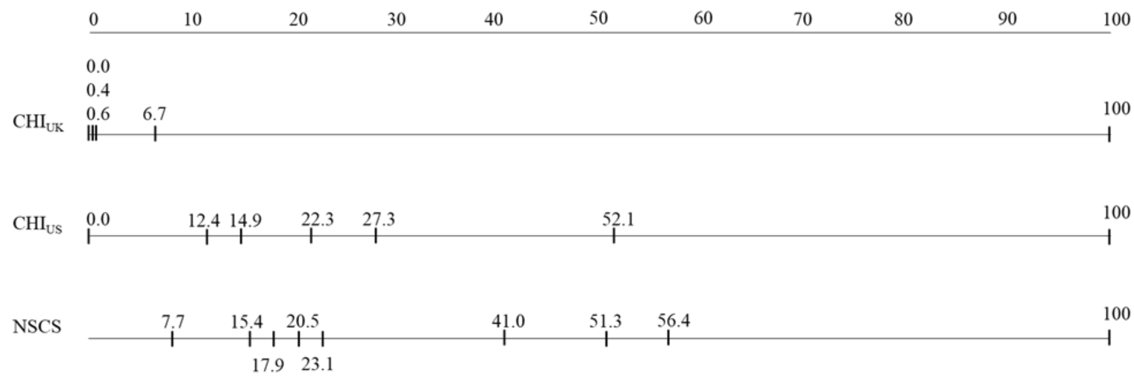


Figure 4.3 Comparison of data point spread within 100-point standardized weighted scales, for the Crime Harm Indices (both U.K. and U.S. versions), and the National Survey of Crime Severity (NSCS) scale.

Of the three harm-weighted crime (harm spot) KDE maps, the one that most closely resembles the unweighted crime (hot spots) map is the NSCS scale. As highlighted earlier, the correlation between these two smoothed distributions is nearly perfect (r=0.99). The high correlation coefficients observed among the four maps are likely the result of the high volume of thefts/larceny crime (76% of all crime). The higher association between the unweighted crime and the NSCS-weighted crime distributions may be attributable to the spread of data points across the NSCS scale (and the difference between the lowest scoring and the highest scoring crime types) is not nearly as drastic as for the two CHI scales (see Figure 4.1).

4.7 Discussion

Study #1 provides the first application of a crime seriousness scale to the spatial analysis of crime in the United States, as well as a systematic comparison of three different weighting scales that can be used in the spatial analysis of crime harm. In line with Weisburd's (2015) law of crime concentration, 80% of crime was spatially clustered within approximately 18% of the area. Harm was equally concentrated (i.e., 80% of harm contained within 16-19% of the area). In contrast to Weinborn et al. (2017), harm was not found to be more spatially concentrated than unweighted crime. It is possible that the different units of analysis (the current KDE map grid cell vs. the street segment in Weinborn et al.'s study) may be responsible for this inconsistency, as well as differences in the crime types considered (see below). Future research should seek to clarify these issues.

The geographic distribution of harm seemed to follow a different non-random distribution compared to the non-random distribution of raw crime counts. For instance, while unweighted crime clustered mostly around the city center, harm appeared to also affect other areas. Having said this, differences were observed among the three crime seriousness scales. The additional hot spots observed in the two CHI-weighted harm spot maps indicated more serious crimes were more prevalent further away from the city center. This implies that focusing on hot spots may indeed reduce the number of crimes, but perhaps draw attention away from more serious and dangerous crimes. The NSCS-weighted harm spot map was the most similar to the unweighted-crime hot spots map, which may be due to the way data points are more evenly spread across this particular scale (see above). Another possibility is that this scale, being based on subjective perceptions of crime seriousness, is a proxy for fear of victimization rather than actual crime seriousness. Further research is necessary to untangle this relationship.

The results of the present analysis indicate that harm may follow different social ecological processes than those underlying the spatial distribution of crime. The majority of crimes occur where most people congregate (Cohen & Felson, 1979; Mayhew & Levinger, 1976; Wirth, 1938). In urban areas, population density – most notably within city centers – leads to more interactions with others, which creates crime opportunities and results in increased crime rates. However, more serious crimes, such as homicide, appear to be *further away from* the city center, where there are potentially fewer people. Further exploration and replication of the geographic correlates of this pattern is necessary to fully understand why this is occurring. Drawing from the tenets of routine activity theory (Cohen & Felson, 1979), it is possible that these crimes are being committed in less visible places (e.g., in the offender or victim's home) where guardianship is low. Other environmental features may also be conducive to more – rather than less – serious crime.

Attention should also be drawn to the similarities of the distributions in the unweighted crime map and the NSCS-weighted crime map. There are several possible reasons for why these maps may be more similar. The first, and most probable, is that the differences between each relative harm score is not as pronounced as it they are in the CHI. With such drastic differences between scores, this creates a sort of "homicide effect" that emphasizes where these crimes are occurring. This can be seen in both of the CHI maps in Figure 4.1, where areas known for gang violence are located in Washington, DC (e.g., southeast of the Anacostia River).

Second, the National Survey of Crime Severity scale was developed by asking respondents to rate crimes by comparing them to a “baseline” offense, which provides the respondents from a starting place. When provided with a comparison of a suggested score for a minor offense, this may change the process by which respondents develop a relative score for other offenses. Having a baseline score to compare to provides a place to move away from versus arbitrarily assigning a score to offenses without any sort of comparison.

A third possible explanation is that this scale is picking up on more than just the harm of the crime, but also the fear of that crime being committed against the respondent and that the fear of any crime may cause an overestimation of the harm that is associated with different offense types. As such, it is more likely that this scale is not as objective in its scores as a CHI scale may be.

Future research should focus on the reasons for why such scores are assigned. This would help better understand why the NSCS scale was distributed in such a way that scores are more reflective of distribution of raw crimes. It would also be enlightening to test the difference between the CHI and scales like the NSCS-based scale within the context of the fear of crime literature. There may be a possible connection to the types of crimes that occur in respondents’ neighborhoods, the crimes being ranked or scored, and the level of fear of crime that someone may have.

A notable strength of the present study is that it is the first test of Sherman et al.’s (2016) CHI in the United States. Harm spot research has typically been conducted outside of the United States, but there are still very few studies utilizing weighted crime counts to determine which areas in a jurisdiction are more dangerous than others. Second, the results of this study indicate that a scale built on the U.S. Sentencing Guidelines generally behaves the same as the CHI built on the U.K. Sentencing Guidelines. While Sherman et al. (2016) have made a suggestion of a feasible harm-weighting index, it still requires testing to determine if it works the same from jurisdiction to jurisdiction. This scale drastically displays the difference between high-harm and low-harm crimes. This is helpful in identifying areas that are more dangerous, and ultimately provides a measure that allows researchers to identify these areas with more precision rather than just using the pure accumulation of unweighted crime to determine areas that are dangerous.

The present research also benefits from the use of an objective measure of harm, as this prevents any bias from the researcher about which crimes are more serious than others. The purpose of this dissertation, and the harm spot literature in general is to provide a way to objectively identify what places are most dangerous based on the types of crimes that are occurring there, rather than simply as the accumulation of raw crime counts. As the scale only utilizes the baseline offense to create the harm scale and eliminates features that classify the offender as the dangerous component, this creates an objective scale that may be best used in research focusing on dangerous locations, rather than dangerous people (though it is arguable that such a scale can be utilized to develop a list of dangerous people, as well).

There are limitations to the present study that should be mentioned. The first is that the data employed are publicly accessible data that lack the nuanced detail required to perform more comprehensive comparisons. For example, the NSCS scale is based on public perceptions of crime seriousness, but the crimes featured in this scale are extremely detailed and compounded by aggravating circumstances when presented to each respondent. Additionally, the most recent test of the original CHI scale by Weinborn et al. (2017) expanded the "menu" of offenses to include all those listed in the U.K. Sentencing Guidelines. The offenses in the present study were limited to UCR Part I Index Crimes and the only detail that was available was whether a weapon was used in the commission of the crime. A possible next step would be to follow the methodology outlined in Weinborn et al. (2017) and construct a full offense "menu" which includes all offense types listed in the U.S. Sentencing Guidelines.

Having said this, the U.S. Sentencing Guidelines are a complex document that requires a significant amount of detail about the offense, and sometimes about the offender, before a suitable sentence (and a crime seriousness score) can be assigned. While the current application of the Guidelines standardized sentencing across similar cases, it also decreased the precision with which the CHI_{US} crime seriousness scale was developed. For example, the crime seriousness score for the homicide category in the Washington, DC, data was based on the sentences for the six subcategories of homicide in the U.S. Sentencing Guidelines. Further, Sherman et al.'s (2016) CHI scale considered information about fines and community service, which likely resulted in more accurate scores for lesser crimes; unfortunately, the U.S. Sentencing Guidelines do not include this information.

4.8 Conclusion

The purpose of Study #1 was to extend the evidence base relating to the spatial patterns of crime-related harm, and also to provide a systematic comparison of crime seriousness weighting scales and their resulting harm spot maps. CHI scales are based on local sentencing guidelines and likely sensitive to cultural variations across countries, as well as whether said countries favor a retributive or a restorative approach to justice. When compared to the subjective scale (NSCS), however, the degree of association decreased, although not enough to be outside the expected range of variation. The real difference appears when harm is visually displayed in the maps. The NSCS-weighted data more closely replicated the visual display of the unweighted crime data, calling in to question the assertion that sentencing guidelines are truly a representation of public opinion. The relationships between the CHI scales and the NSCS scale are fairly strong, but the strongest relationship was between the NSCS scale and the unweighted crime data. Additionally, crime-related harm also concerns the economic cost to society, and/or to the victim, and can result in varying degrees of personal injury which may not necessarily be considered in suggested baseline sentences.

The CHI scales provided a stronger distinction between higher-harm and lower-harm offense types and their continued use is suggested, but so too is research exploring alternative ways of measuring crime-related harm. The CHI provides an objective tool for simply looking at offenses to determine how dangerous a place is based on the types of crimes that occur, while simultaneously accounting for the obvious differences between each crime type. Additionally, one can expect that a CHI based on U.S. Sentencing Guidelines' recommendations is likely to closely replicate the results of a CHI based on the U.K. Sentencing Guidelines. This, at minimum, provides a preliminary test of the validity of a U.S. Sentencing Guidelines-based CHI.

5. PATTERNS OF CRIME HARM: REPLICATIONS OF HARM SPOT STABILITY IN TIME AND SPACE

5.1 Abstract

Recent attention to the use of harm indices to weight crime counts in mapping analysis has led to the development of "harm spot" maps. The existing literature has focused on the spatial concentration of harm (Weinborn et al., 2017), the comparison of the spatial distributions of different weighting scales (Study #1; Chapter 4), the concentration of harm among recorded offenses (Norton et al., 2018), and the stability of harm spots over time (Norton et al., 2018). The results of Study #1 (Chapter 4) suggested that: 1) the use of a Crime Harm Index (CHI; Sherman et al., 2016) derived from the U.S. Sentencing Guidelines closely approximates the distribution using the index developed by Sherman et al. (2016) using the U.K. Sentencing Guidelines; and 2) harm spots are diffused away from the city center into more residential areas. In other words, there was a different non-random spatial distribution of crime for crime harm versus crime volume. This implies opportunities for more serious offenses could be higher in residential areas, and that different social ecological processes underlie the spatial distribution of more – versus less – serious crime. Having said this, replication is necessary before…. Study #2 replicates and extends the previous research exploring the spatial, temporal, and spatiotemporal distributions of harm spots using police-recorded crime data for Austin, Texas.

5.2 Introduction

Research on the spatial analysis of crime has established that crime concentrates in time, space, and people. In particular, it is now a theoretical law that the majority of crime is caused by very few people and at very few places (Weisburd, 2015). Crime follows a non-random geospatial pattern, whereby it concentrates at particular locations known as hot spots (Sherman et al., 1989). In the last few years, researchers have begun to experiment with weighting crime by a relative harm score to examine the distribution of crime harm within a jurisdiction.

The idea that crime should be weighted based on seriousness to fully understand the effect it has on communities has been recently applied to hot spot maps, which tend to consider crime patterns at a micro level. The findings that have been produced from these studies are limited and have yet to be replicated. The purpose of Study #2 is to further explore the use of Sherman et al.'s (2016) Crime Harm Index (CHI) using U.S. Sentencing Guidelines and to determine if what has been reported in the existing literature replicates using reported offenses from Austin, Texas.

Study #2 is structured as follows: first, the existing literature is reviewed surrounding harm spot mapping. The focus is more narrowly constructed on the three studies that have previously provided a geospatial analysis of harm spots and the findings that have been reported. This section is followed by the methodology, including data sources, variables, and analytical strategy. The chapter ends with a discussion of the strengths and weaknesses of Study #2.

5.3 Literature Review

There is "[a] strong body of evidence [that] illustrates the concentration of crime in unique places called hot spots… [research has] shown that crime is not a random event and that there is 'some-thing' about certain places that attracts crime and disorder" (Weinborn et al., 2017, p. 232). However, not all hot spots are created equal. For example, two hot spots may have an equal number of crimes, but one could consist solely of bicycle thefts, while the other may disproportionally consist of aggravated assaults. Using current policing practices, both would receive equal treatment based on the *number* of crimes that occurred, rather than where crime was causing more *harm*, leading researchers to begin to investigate harm spots. Only a few studies have been completed examining harm spots. The first examined the concentration of harm when compared to the concentration of raw crime counts (Weinborn et al., 2017). This particular study pioneered the technique of mapping crime through an additional dimension of harm in order to compare the concentration of raw crime counts to harm weighted crime in the United Kingdom. They developed a full "menu" of criminal offenses based on the U.K. Sentencing Guidelines and mapped the more detailed version of Sherman et al.'s (2016) index. The authors reported that 50% of crime harm concentrated in fewer addresses (1% versus 3%) than 50% of raw crime counts, indicating that crime harm is only slightly more concentrated in space than crime volume.

Study #1 (Chapter 4) reported no notable difference between the spatial clustering of harm-weighted offenses and unweighted offenses. The degree of spatial clustering was comparable to that reported by Weinborn et al. (2017). The comparison of spatial concentration between the three different harm weighting scales and the unweighted offenses was performed by using the grid cells of the kernel density estimation map grid as the unit of analysis. The level of concentration was determined to be generally the same for each of the three weighting scales and the unweighted offenses. Almost uniformly, 80% of harm was concentrated within approximately 18% of the total grid cells for all three of the harm weighting scales. Approximately 80% of the crime volume occurred within the same number of grid cells.

Hot spots that are identified on crime volume alone may not necessarily be the most "dangerous." For example, Boivin (2014) criticized the annual list of dangerous cities in Canada for being incorrectly calculated, simply because these lists are typically based on raw crime counts and fail to account for the relative harm score of each offense. Statistics Canada (Babyak et al., 2009) has developed a formula to create a relative harm score based on Canadian sentencing data from the preceding five years, but this equation still fails to account for crime volume and, therefore, misrepresents the dangerousness of urban areas. Boivin (2014) offered a solution to this problem which included accounting for the number of offenses that occurred when calculating the "dangerousness" of cities in Canada. His revised equation resulted in a list of dangerous cities that was nearly inverted once the harm of each offense was properly accounted for in the dangerousness calculation. However, the disparities in findings are likely a result of the difference in the methodologies that were used. This further underscores the need for replication of findings in this new direction of research exploring the spatial distributions of crime harm, as well as consensus on the best measure of harm.

Both Weinborn et al. (2017) and Study #1 (Chapter 4) have explored the spatial clustering of harm-weighted offenses and have concluded that the spatial patterning of harm spots and high-volume is generally comparable, but that harm appears to be more diffused from the city center than raw crime counts. Norton et al. (2018) further explored the concentration of harm by identifying the crimes that were responsible for the majority of the harm, as well as the temporal patterns of harm spots. Their results indicated that harm clusters in the winter, during the weekends, and peaks in the late afternoon/evening hours. In other words, the clustering of crime harm varies over different temporal periods, and often displays a different pattern from raw crime patterns. This analysis lacked a geographic component, and therefore, did not show how crime harm clusters in space over time.

More importantly, using Sherman et al.'s (2016) CHI, the studies based on the scores developed from the U.K. Sentencing Guidelines (Weinborn et al., 2017) and the U.S. Sentencing Guidelines (Study #1; Chapter 4) resulted in a distinct non-random spatial pattern of crime harm. This pattern emphasized that offenses with a high relative harm score rarely occurred, but created distinctive harm spots at the locations where these offenses were. It also illustrated the tricky relationship between harm spots and the volume of offenses with low-harm scores. It was observed that, by virtue of pure accumulation of data points, these locations similarly became more pronounced harm spots. There are likely social implications and explanations for these findings, but such findings should be investigated further and replicated in other settings before any recommendations are made.

5.4 The Current Study

Study #2 served to further explore the spatial distribution of crime harm through a replication of Study #1 (Washington, DC), but relying on data from Austin, Texas. As findings regarding harm-weighted crime and its spatial distribution are still extremely limited, replication is an important next step in the literature. Currently, research has indicated conflicting evidence suggesting 1) that raw crime counts and crime harm are equally clustered in space (Study #1; Chapter 4), and 2) that harm is more concentrated in space than raw crime counts (Weinborn et al., 2017). Norton and colleagues (2018) also reported that 70% of street segments designated as harmspots remained in the top 50 most harmful street segments over four years. So far, these are isolated findings that have yet to be replicated.

Study #2 seeks to replicate previous research from both Study #1 (Chapter 4) and Norton et al. (2018). A kernel density estimation map was produced following the same methodology used in Study #1 (Chapter 4), which includes creating a weighted crime scale and using these data to create two KDE maps for all recorded crime in Austin, Texas, from 2007 to 2017. Second, temporal patterns of clustering were explored by plotting the percent of total crime and total harm on graphs using a simple bivariate analysis over the course of a year, month, week, and day. These temporal trends were also compared to the average harm score for each different time period. Finally, a series of six KDE maps were produced to explore the spatiotemporal concentration of raw crime and harm between 2011 and 2015.

5.5 Methods

5.5.1 Data Sources

Geocoded crime data recorded for Austin, Texas are used in the present study. These data include the address, geographic coordinates, date, and time of every offense reported to the Austin Police Department (APD) between the years of 2007 and 2017 (N = 145,729 offenses). These data *only* included Part I Index Crimes reported in the city of Austin for this time period, excluding those Index Crimes that were family and domestic violence cases. As APD can be tasked with responding to crimes in jurisdictions bordering the city's official boundaries, these crimes were further reduced to only include those which were reported to have occurred within the department's official jurisdiction. This resulted in a final sample size of 145,571 reported offenses.

The eight crime types included in Study #2 are all UCR Part I Index crimes, namely arson, assault with a dangerous weapon (aggravated assault), burglary, forcible rape/sexual assault, homicide, larceny-theft, motor vehicle theft, and robbery. APD submits their reported crime data to the UCR and NIBRS each year, and records these categories in their publicly available data. This resulted in crime categories which better matched the offenses used in Sherman et al. (2016) and Study #1 for replication and consistency. These categories, with their corresponding number of recorded crimes, are listed in Table 5.1.

Table 5.1 Number and percentage of offenses between 2007 and 2017 (inclusive) in Austin, Texas, and corresponding raw and standardized crime weights for the CHI_{US} crime seriousness scales, by crime type.

	Recorded crime		CHI_{US} scores[a]		
	N	%	Raw	Std.	%
Property Offenses					
Arson	707	0.49	1,230	11.39	2.95
Burglary	19,048	13.09	495	4.58	31.97
Larceny-theft	110,343	75.80	30	0.28	11.22
Motor vehicle theft	6,817	4.68	810	7.50	18.72
Violent Offenses					
Aggravated assault	4,939	3.39	720	6.67	12.06
Homicide	89	0.06	10,800	100.00	3.26
Rape/Sexual assault	547	0.38	2,910	26.94	5.40
Robbery	3,081	2.12	1,380	12.78	14.42
Total	145,571	100.00	29,491,260	273,270.6	100.00

[a] Scores were calculated using the U.S. Sentencing Guidelines (see Appendix 3).

These data maintain consistency in the methodologies between Study #1 and Study #2. Other data options exist that would provide perhaps a better idea of the harm experienced within neighborhoods. For example, using calls for service may actually enhance the analysis of harm spot mapping. However, the data in Washington, DC only included officially reported offenses classified in nine broad UCR Part I Index Crime categories (with larceny-theft divided into to two separate categories), similar to those that were included in the original description and test of the CHI (Sherman et al., 2016).

5.5.2 Crime Harm Weighting Scales

The weighting scale utilized in Study #2 was created following the procedures presented by Sherman et al. (2016) and using the U.S. Sentencing Guidelines. The original scale was created using the U.K. Sentencing Guidelines as the Cambridge Crime Harm Index (CHI; Sherman et al., 2016). Because the results in Study #1 indicated that the CHI based on the U.S. Sentencing Guidelines closely resembles and behaves similarly to the CHI based on the U.K. Sentencing Guidelines, the U.S. index was used for both Study #2 and Study #3 (Chapter 6) to weight each crime by its relative harm score.

There are three requirements that must be met for the construction of a crime harm index. It should be democratic (reflect the will of the people), reliable (can be consistently applied), and be cost-effective for the agencies implementing it. The use of the U.S. Sentencing Guidelines to construct a weighting scale passes this three-pronged test (Sherman et al., 2016) and it “offers the lowest cost and [the] greatest speed. It is readily available to be applied to any set of crimes” (p. 177). The weights can then be constructed using the recommended sentences based on the sentencing table. Sherman and colleagues (2016) provide the following steps to construct this scale.

1. *Identify the starting point sentence.*

This should be based on the offender having no prior convictions. The logic in this is that basing the score on offenders' prior convictions retains the focus on the harm of the offense, and not on the offenders' behaviors. Society is harmed by a crime whether it is the offender's first offense or if they are a repeat offender.

2. *Convert the recommended sentence to the number of days served.*

The U.S. Sentencing Guidelines recommends sentences by months in prison. Therefore, each of these recommended sentences was multiplied by 30 to create the unstandardized harm scores provided in Table 5.1.

3. *If the minimum sentence is recommended as hours or days of community service, this is also converted to the number of days "served."*
4. *If the minimum sentence is a fine, the number of days is calculated by the number of days it would take to pay this fine working for minimum wage.*

The U.S. Sentencing Guidelines only provides recommendations for the number of months to serve in the sentencing table. As such, Steps 3 and 4 are only implemented when this information is available. The minimum recommended sentence for theft is no months served, and this is likely due to the fact that community service or fines are suggested punishments for an offense with such low seriousness. This is why a sentence of 30 days was used for all larceny-theft cases in the present study.

The scale was recreated using the more nuanced data available in Austin, and was recreated to include a harm score for larceny-theft offenses. In Study #1, these offenses were essentially unweighted, as the minimum sentence suggested for these cases was 0 months. However, it is arguable that some punishment is received for those larceny-theft cases that are prosecuted, and so a score associated with one month was assigned to these crimes. Once the CHI scale was finalized for the Austin data, it was standardized into a 0-100 proportional scale. It is this transformed scale that were used to create the harm-weighted kernel density estimation (KDE) maps in the present study. These scores are presented in Table 5.1.

The CHI constructed by Sherman et al. (2016) and the CHI constructed using the U.S. Sentencing Guidelines displayed a degree of similarity, which indicates that these scales are performing in a similar way (Study #1, Chapter 4). The crime harm scores are slightly different between Study #1 (Chapter 4) and Study #2, and this is largely due to the fact that data from APD provided more nuanced information to understand the sub-categories of crime that are included in the broad UCR Part I Index Crime categories. The median scores of all crime sub-types were then used to calculate the harm score for each Part I offense category (see Table 5.1 and Appendix 3).

The CHI has not been consistently constructed in past research. Study #1 and Study #2 closely follow the original description of the CHI (Sherman et al., 2016), using broad UCR Part I Index Crime offense categories and the native country's baseline sentencing guidelines. Other studies have attempted to expand the CHI to include a wider variety of offenses and to assign a relative harm score to *all* offenses that are included in police calls for service in New Zealand (Curtis-Ham & Walton, 2017a) and the United Kingdom (Weinborn et al., 2017). These extended indices calculated scores for all crimes that fall within the larger categories that were presented in Sherman et al. (2016).

Additionally, scores are not fully comparable as they have not been calculated consistently using the same, or similar, sources for the harm calculations. Curtis-Ham and Walton (2017a; 2017b) used existing sentencing data to calculate scores from sentences that offenders *actually* received for each of the offenses that were used in the study. Alternatively, Weinborn et al. (2017) used the U.K. Sentencing Guidelines and constructed a harm score for every offense that is included in the sentencing guidelines, following the steps provided by Sherman and his colleagues (2016).

5.5.3 Analytic Strategy

The analysis of these data occurred in several phases. The first phase consisted of descriptive statistical analyses, as well as supplemental analyses to ensure data quality. The results of the supplemental analyses are presented in APPENDIX C – Supplemental Analyses. This included the types and the frequencies of each type of crime. The next phase of this analysis consisted of creating a KDE map for all offenses between 2007 and 2017, both raw and weighted. ECDF graphs were used to supplement the comparison of these two maps.

The next phase of this analysis consisted of addressing the stability of harm spots over time in a replication of Norton et al.'s (2018) study. This consisted of examining the percent of total crime and total harm, and the average harm score for all eleven years of aggregated data over several different time intervals, including across all years, months of the year, days of the month, a week, a day, and across shifts. The final phase considers both time and space simultaneously by generating a series of KDE maps for different time intervals to determine if the clustering of harm remains concentrated in the same places over time.

5.6 Results

5.6.1 Descriptive Analysis

The data were cleaned and prepared for geographic and temporal analyses in ArcGIS Pro. The sample size ultimately changed depending on the unit analysis and the number of valid cases for a particular analysis. However, once the data were cleaned a total of 145,729 cases were available to analyze. The distribution of these Part I Index Crimes is displayed in Table 5.1.

Figure 5.1 displays the percent of total crime and total harm for better comparison of how each Index Crime is distributed. Larceny-theft offenses makes up the majority of all offending between 2007 and 2017, but it only accounts for approximately 12%. Burglary accounted for nearly one-third of all harm (31.97%) and more than any other single crime category, while it only accounted for 13% of all crime that occurred by tween 2007 and 2017. Property offenses accounted for the majority of reported offenses (94.06%) and the majority of total harm (64.86%) for the time period examined.

These results are consistent with previous research, finding that each crime categories' contribution to the total inverted when considering the total harm rather than the total crime. Similarly, Norton et al. (2018) found that the counts of crime and the harm inverted for theft offenses, sexual offenses, and robbery, and Weinborn et al. (2017) found similar findings for homicides, rape, and robbery. Figure 5.1 displays similar results. They state that "[n]ot all high-volume crimes are indicative of low-harm scores; theft and handling…are so prevalent that they are responsible for 15%...of crime harm…" (Norton et al., 2018; p. 358). In the present study, theft accounts for nearly 12% of all harm purely by accounting for 75% of all crime reported between 2007 and 2017.

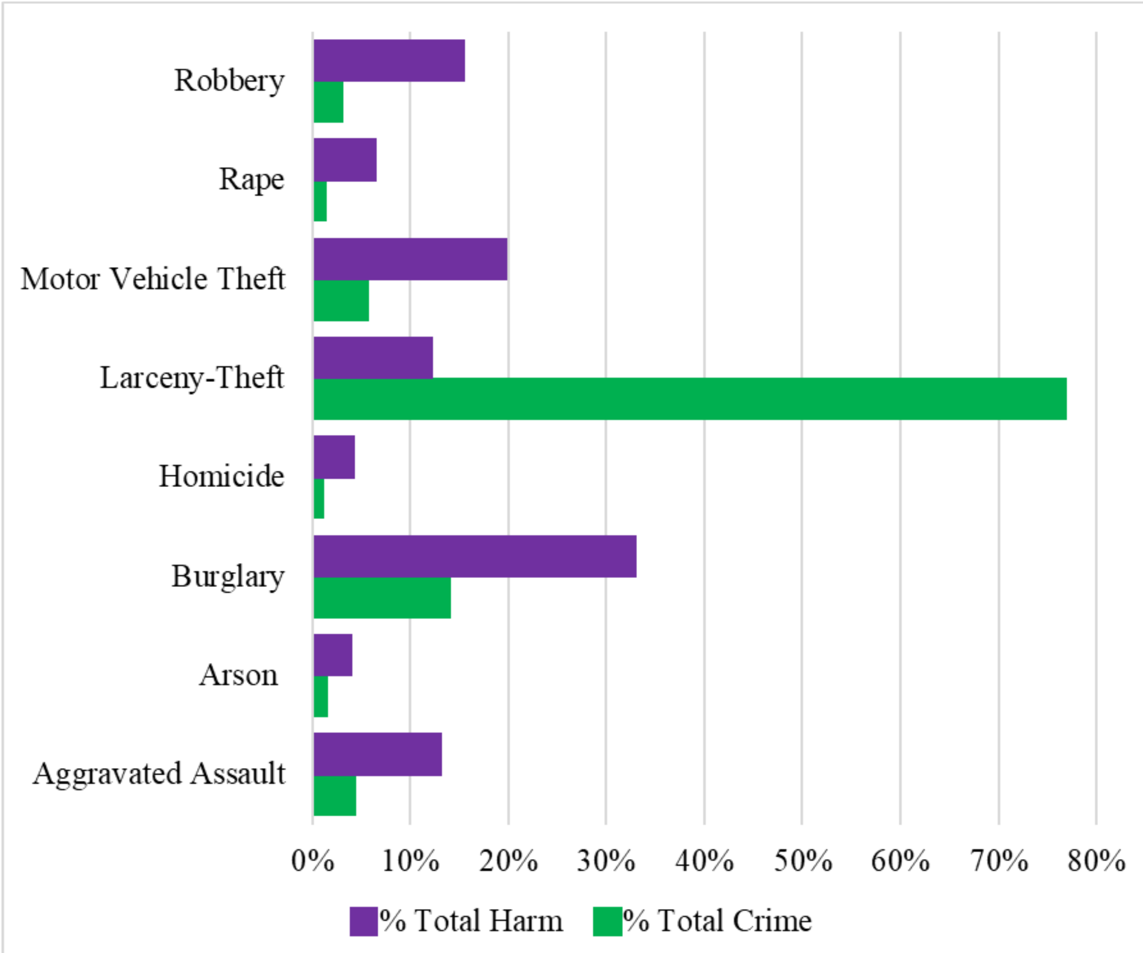


Figure 5.1. Comparison of percent of total crime and total harm for each Part I Index Crime in Austin, Texas, from 2007 to 2017.

5.6.2 Spatial Distribution of Harm

The spatial analysis consisted of examining the spatial distribution of raw crime counts and crime harm through the use of kernel density estimation maps. Kernel density maps provide a geographic histogram that identifies modal points of crime incidences, which is generally a method of identifying hot spots of crime volume. These histograms are then smoothed over, similar to plotting a density curve over a histogram. This smoothing process then provides a map with a color gradient that identifies the "heat" in different areas of the map. The hottest spots are therefore the areas where the most crime occurs. For the present study, the option to include a weight for each point was utilized to change the map from measuring volume, where every point is of equal weight, to measuring the additive effect of harm, where every point is weighted by the relative harm that a crime may cause.

One limitation should be mentioned before describing the results. KDE operates on the assumption that the scores on the outside of the jurisdictional boundary are correct and uses these null values to calculate the density at the border. The data in Study #2 (Chapter 4) and Study #3 only include crimes that occurred within the APD jurisdictional boundaries. The hot spots along the boundary are, therefore, to be underestimated, causing a boundary effect, or inaccurate density estimates. Results at the edge of each map in Study #2 should be interpreted with this limitation in mind.

Figure 5.2 displays the results of the hot spot map for all unweighted Part I Index Crimes in Austin between 2007 and 2017. As expected, the highest density of crime counts occurs in the downtown areas. Figure 5.3 displays the results of the harm spot map for all weighted Part I Index Crimes between 2007 and 2017. When examining the spatial distribution of harm-weighted crime in Washington, DC, different non-random patterns were observed between the unweighted and weighted crimes. However, both maps in the present study appear to follow the same spatial patterns. This is inconsistent with previous findings (Study #1, Chapter 4).

It is clear that crime volume and crime harm generally cluster along the main interstate that runs through Austin (I-35) (see Figure X). This interstate runs from Laredo, Texas, at the border of Mexico and the United States, to Duluth, Minnesota. It passes through many major urban areas, including San Antonio, Austin, Waco, Dallas-Fort Worth, Oklahoma City, Wichita, Kansas City, Des Moines, and Minneapolis/St. Paul.

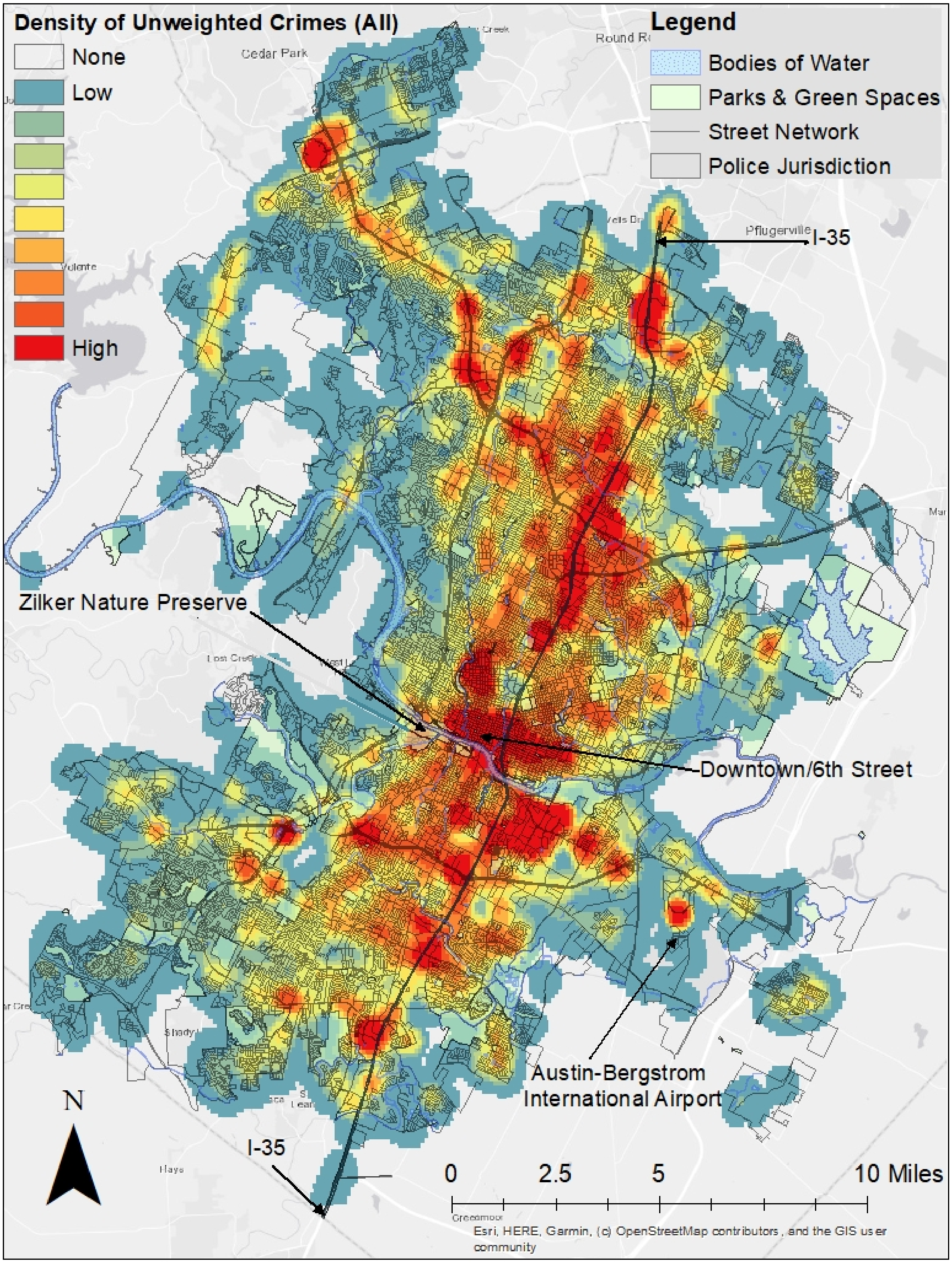


Figure 5.2. Kernel density estimation map of all unweighted Part I Index Crimes in Austin, Texas, from 2007 to 2017.

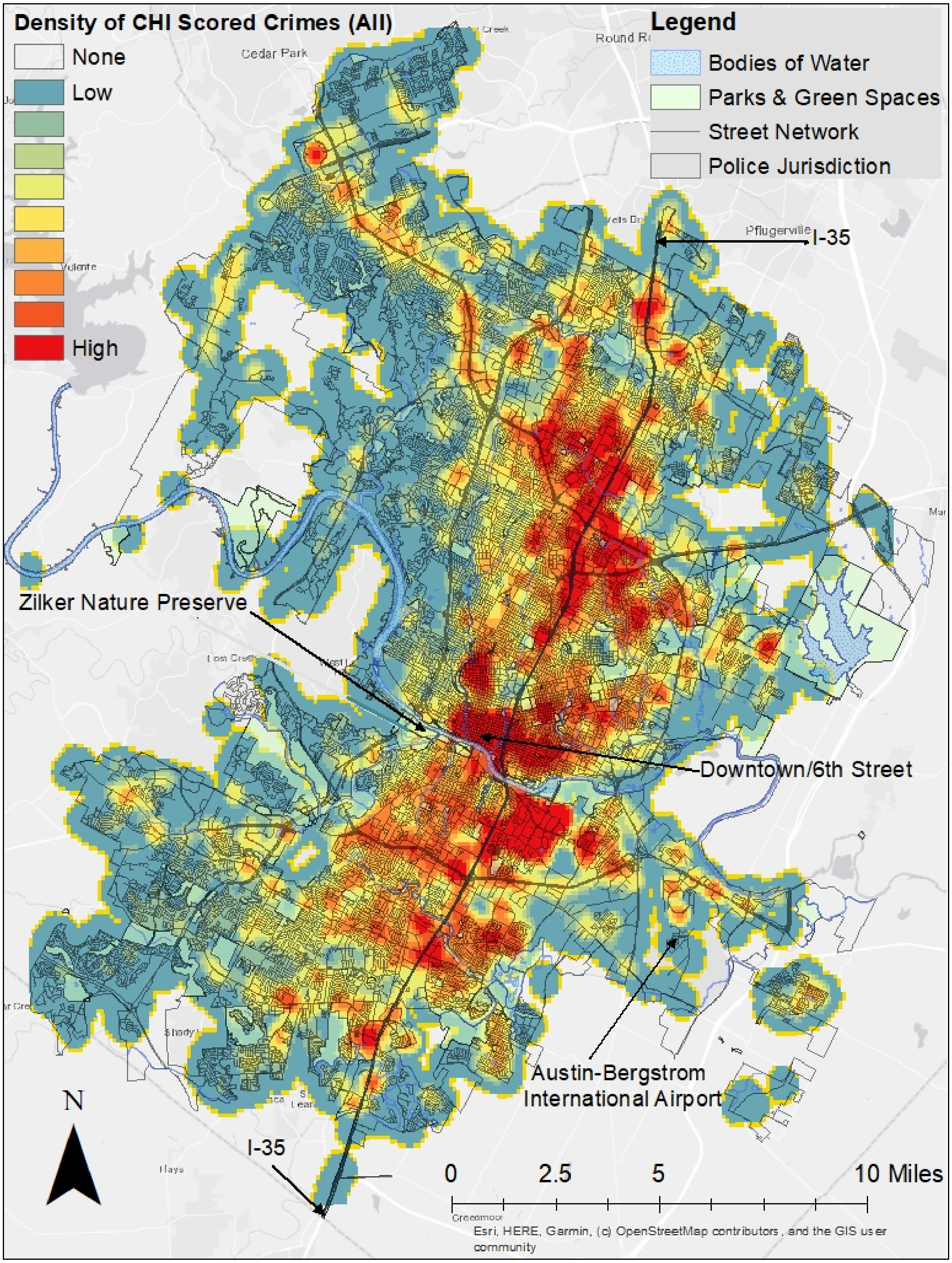


Figure 5.3. Kernel density estimation map of all weighted Part I Index Crimes in Austin, Texas, from 2007 to 2017.

The Texas Department of Public Safety has identified I-35 as a major artery for smuggling drugs and human trafficking. Austin is bisected by the interstate, and it operates as a major traffic artery in the downtown area. The accessibility and location of a large clustering of crime generators and attractors in the downtown area (e.g., 6th Street is often filled with bar patrons, and often gets shut down during the South By Southwest (SXSW) or Austin City Limits (ACL) music/film/tech festivals, and conventions draw large numbers of tourists to the city). When being weighted by the CHI, most crimes with high scores generally cluster around primary and secondary interstates and highways. Only a few hot spots do not follow this general rule.

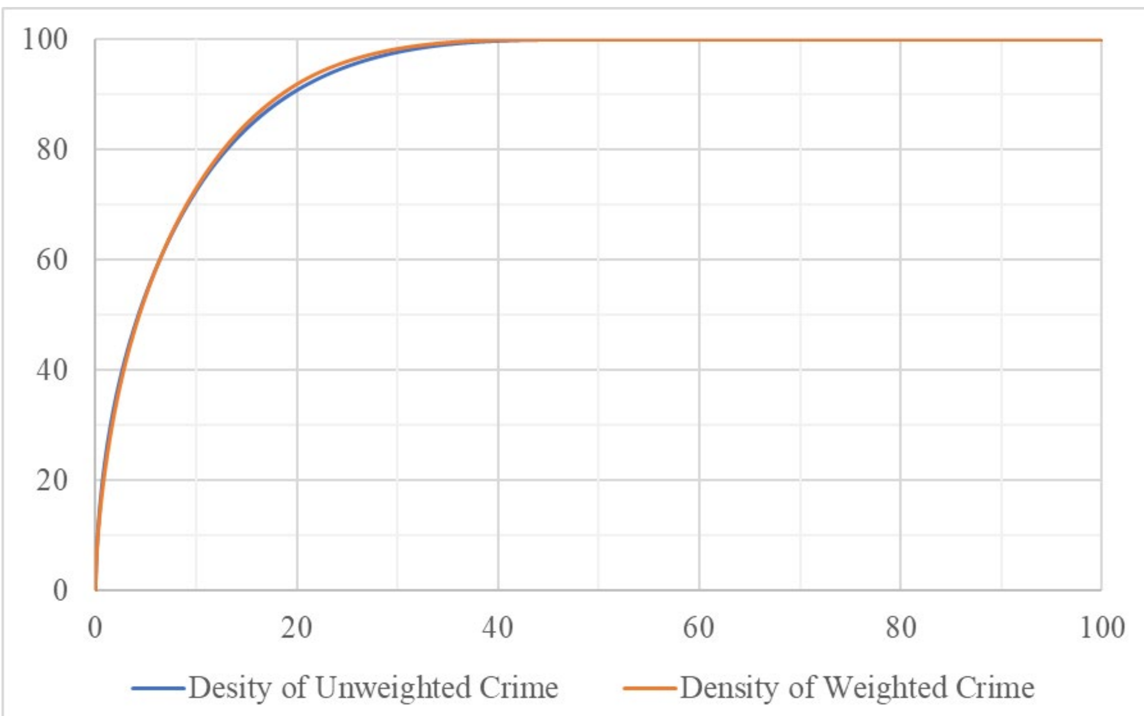


Figure 5.4. Spatial concentration of unweighted and harm-weighted crime, using KDE cell density values as the unit of analysis (N = 64,390 raster cells).

An empirical cumulative distribution function (ECDF; Figure 5.4) was again used to examine the spatial concentration of unweighted and weighted offenses. These maps also display nearly the same degree of spatial concentration, in which 80% of unweighted and weighted crime are concentrated within approximately 13% of the total number of raster grid cells in the unweighted (13.02%) and weighted (12.71%) KDE maps, which is more or less consistent with previous research (Study #1, Chapter 4; Eck et al., 2005; Eck, Clarke, & Gurette, 2007; Sherman, Gartin, & Buerger, 1989; Weisburd, 2015). One hundred percent of all crime and harm occurs within approximately 35% of all cells, indicating that both crime and harm are concentrated in a relatively small number of places in Austin.

While these findings are unexpected based on the results in Study #1 and Weinborn et al. (2017), the present study excludes family and domestic violence cases. There was no ability to identify these crimes in the data from Washington, DC. As such, because these offenses include crimes that are more likely to have higher relative harm scores, these offenses may have been the driving component to the non-random distribution observed in the Washington, DC, data. Supplemental analyses (not presented) indicated that even when the larceny-theft offenses reported between 2007 and 2017 are removed, the KDE maps for both the unweighted and weighted crime follow a very similar

5.6.3 Temporal Distribution of Harm

Percent of total crime, percent total harm, and the average standardized harm score over the course of a day, shift, week, month, a single year, and for the full data set between the years of 2007 and 2017 were examined to identify temporal patterns of clustering in harm scores. One case was coded as missing for the temporal analyses due to a data entry error for the time/date that the offense occurred, resulting in a sample size of 145,570 Part I Index Crimes.

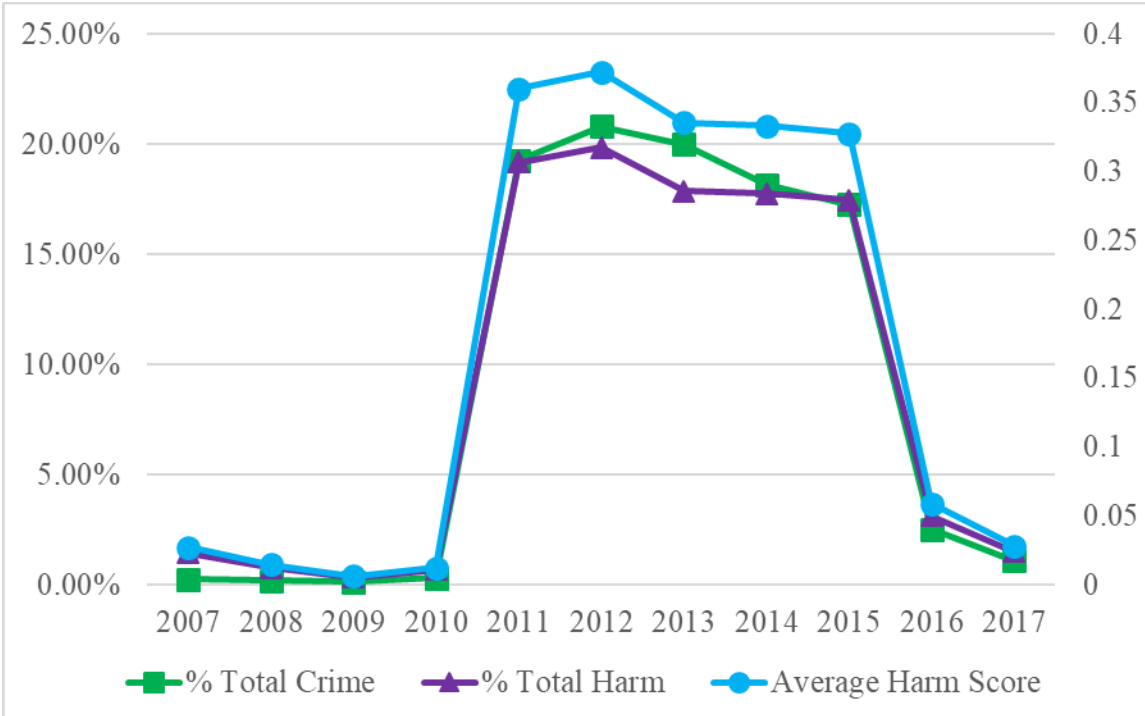


Figure 5.5. Percent of total crime, percent of total harm, and average harm score for all Part I Index Crimes in Austin, Texas, from 2007 to 2017 (by year).

Figure 5.5 through Figure 5.10 display the results of the temporal analyses comparing the percent of total harm, percent of total crime, and average standardized harm score. There is a degree of difference between the number of cases recorded to have occurred in each year. The number of cases between the years of 2007 and 2010 are approximately 500 or fewer per year, while between the years of 2011 and 2015, there are well over 25,000 cases recorded for each of these years. Finally, in the years of 2016 and 2017, fewer than 4,000 cases were recorded. When compared to the official UCR data, none of these years are complete in terms of the number of crimes that were reported for each year.

It is possible that other circumstances and historical events within the city of Austin may have contributed to this trend, such as a change in dispatching, responding, or recording practices. However, no known changes in policies have occurred that would have crime reporting. Other reasons may be that open cases are not reported in the publicly available data, and the data for the present dissertation excludes several cases, including both family and domestic violence APPENDIX C – Supplemental Analyses provides a more comprehensive supplemental examination of these data. Despite this, the data between 2011 and 2015 follow the same general clustering patterns that the official UCR data follow. For this reason, these years are used in the spatiotemporal analysis below.

The total percent of crime harm and total percent of crime are nearly equally distributed between each year, with a slight decrease in both from 2011 to 2015. This is despite a general increase in the population in the city of Austin over the years of data included in this study. In 2007, the city's population was approximately 720,000, and in 2017, the population had risen to nearly 972,000. The average standardized harm score also exhibited a decreasing trend between 2011 and 2015 (which is also observed in the UCR data; see APPENDIX C – Supplemental Analyses).

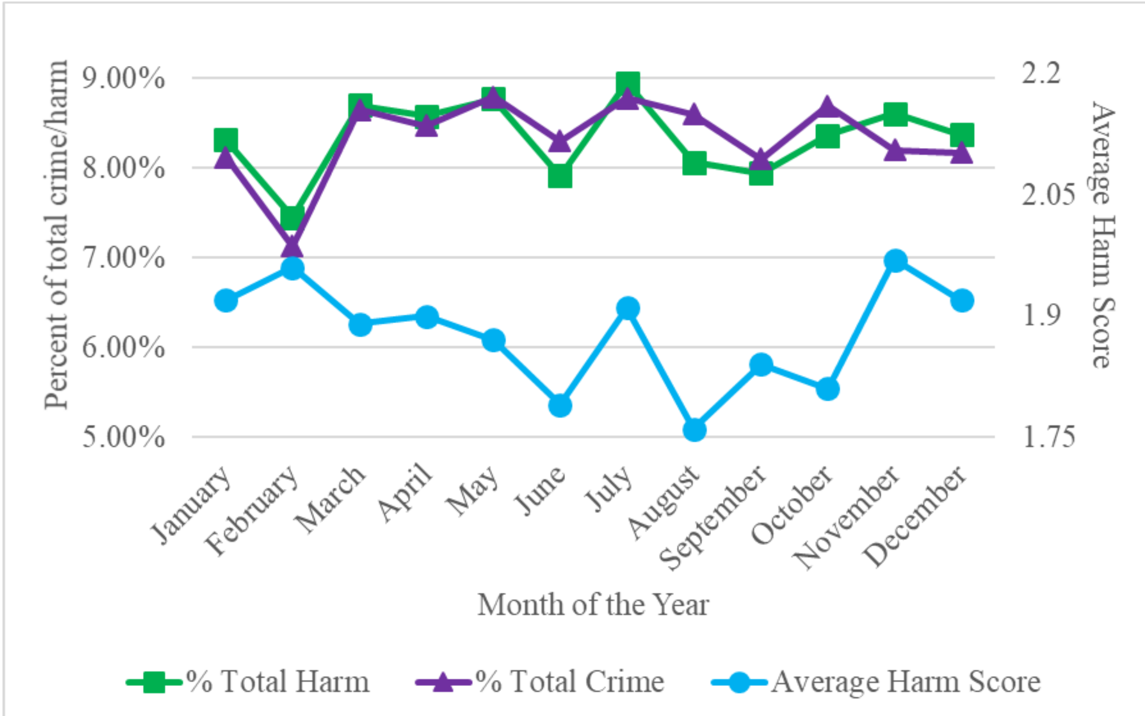


Figure 5.6. Percent of total crime, percent of total harm, and average standardized harm score for all Part I Index Crimes in Austin, Texas, from 2007 to 2017 (by month of the year)

Both the percent of total crime and the percent of total harm followed similar patterns over the course of a calendar, ranging from approximately 8% to 9% (Figure 5.6). The exception to this was February. However, this may be attributed to this being the shortest month of the year. The percent of total harm was highest in the month of July, and the lowest was reported in the month of June. The percent of total crime was also highest in July, but the lowest was reported in January. When compared to the average standardized harm score, the summer months (May to September), with July being the only exception again, had the lowest average standardized harm scores, while the winter months saw a notable increase in the average harm score. This may be related to the more temperate and tolerable temperatures experienced in Austin between October and May (Linning, 2015; Linning, Andresen, & Brantingham, 2017).

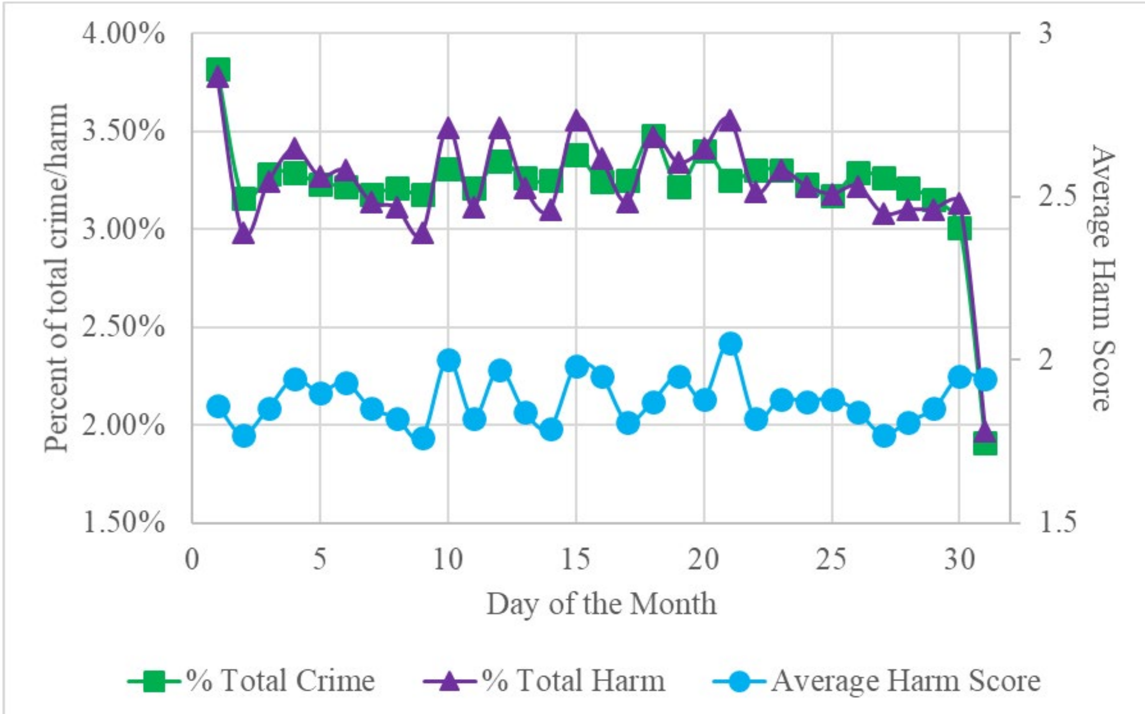


Figure 5.7. Percent of total crime, percent of total harm, and average standardized harm score for all Part I Index Crimes in Austin, Texas, from 2007 to 2017 (by day of the month).

Figure 5.7 displays the clustering patterns of the percent of total crime, percent of total harm, and the average standardized harm score over an entire month. There is no real noticeable trend, with the exception that for both total crime and total harm, the highest percentage was recorded on the first day of each month, while the lowest was on the last day of each month. The lowest percentage for both total crime and total harm was reported on the 31st of the month, but this low recording value is likely due to the 31st of each month occurring less than every other date throughout the year. Similarly, there is no real discernable pattern in the average standardized harm score. However, between the 9th and the 22nd there is a more pronounced degree of variability in the day-to-day difference in the average standardized harm score.

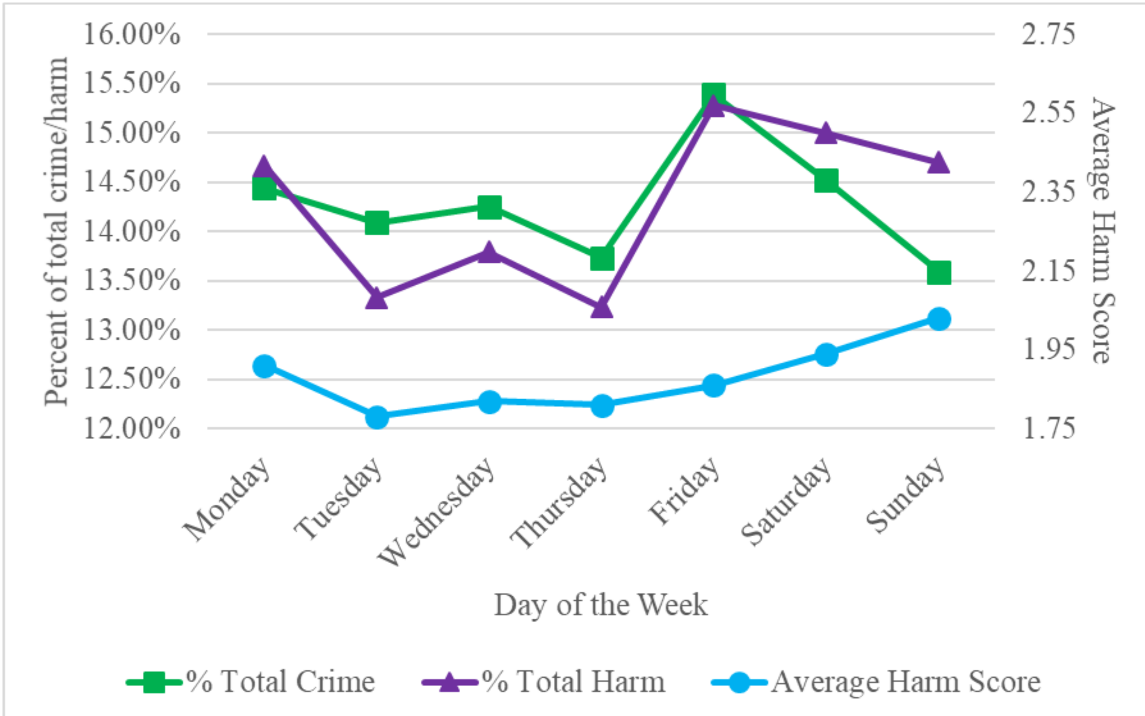


Figure 5.8. Percent of total crime, percent of total harm, and average standardized harm score for all Part I Index Crimes in Austin, Texas, from 2007 to 2017 (by day of the week).

Figure 5.8 displays the clustering of the total percent of crime, total percent of harm, and the average standardized harm scores over the week. Again, both the total percentage of crime and the total percentage of harm, followed similarly patterns from Monday to Sunday, with the highest percentages reported on Fridays and the lowest reported on Thursdays for both total crime and total harm. The highest average standardized harm score was recorded on Sundays, while the lowest average standardized harm score was recorded on Tuesdays. These findings are again consistent with previous research (for example, Andresen & Malleson, 2015). When examining total crime counts, the most crime was frequently observed to occur on the weekends, but they also suggested examining the weekly variation of disaggregated crime types, as different patterns emerged when examining specific offenses (Andresen & Malleson, 2015).

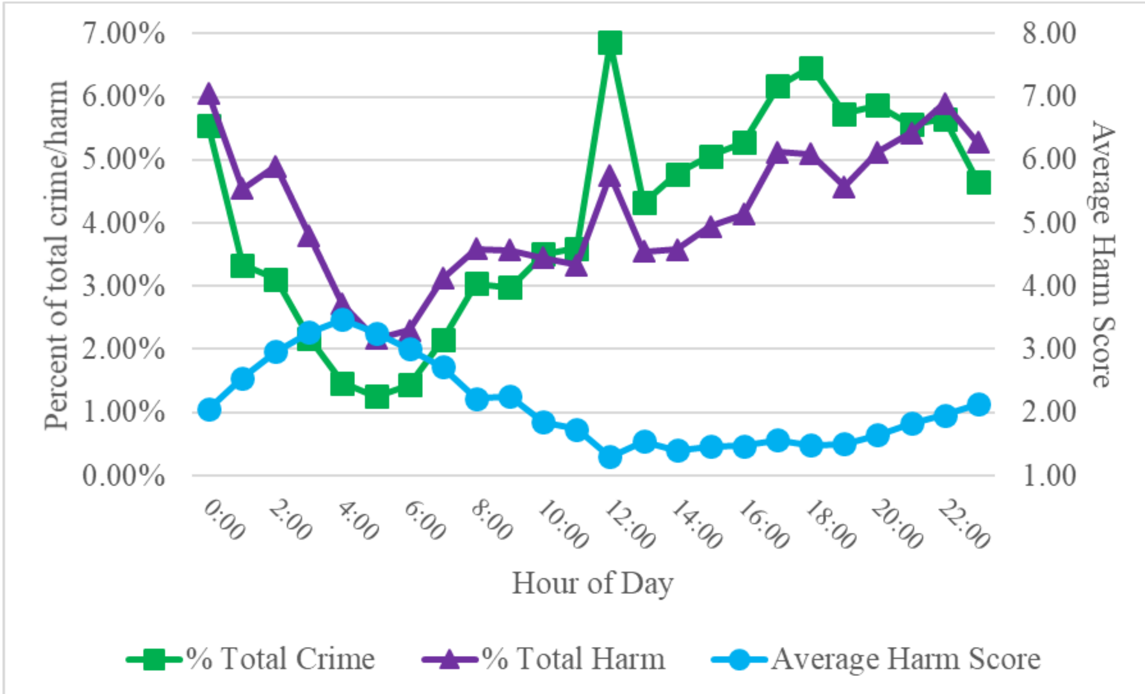


Figure 5.9. Percent of total crime, percent of total harm, and average standardized harm score for all Part I Index Crimes in Austin, Texas, from 2007 to 2017 (by time of day).

The distribution of raw accumulated crime over the course of a day (Figure 5.9) varied expectedly, with the fewest number of offenses being recorded between the hours of 4:00 AM and 7:00 AM, and the largest number of offenses occurring between the hours of 4:00 PM and 11:00 PM. The pattern of the percentage of total crime and total harm is also nearly perfectly consistent with the pattern presented by Weinborn et al. (2017), in which both crime and harm were lowest in the early morning hours (approximately between 4 AM and 7 AM), and highest just before midnight. Both the data from the present study and from the UK (Weinborn et al., 2017) display the dramatic increase in both the percentage of total crime and the percentage of total harm at noon. The average standardized harm score displays a notably different pattern than the percentage of total crime and total harm (Figure 5.9). The highest average crime scores were reported between 3 AM and 5 AM, with the lowest being reported between 11 AM and 1 PM.

These findings are consistent with previous research that has found that a significant number of offenses occur in the hours after schools let out, specifically when latch-key adolescents are unsupervised before parents get home from work (for example, Gottfredson, Gerstenblith, Soulé, Womer, & Lu, 2004; Gottfredson, Gottfredson, & Weisman, 2001). Additionally, crime begins to increase as routine activities begin to shift into nighttime entertainment activities. According to Lemieux and Felson (2012), leisure activities such as these increase risk of violence victimization significantly, specifically when compared to out-of-the-home activities such as working or shopping. Noon and midnight were also hours with noticeably higher recorded offenses.

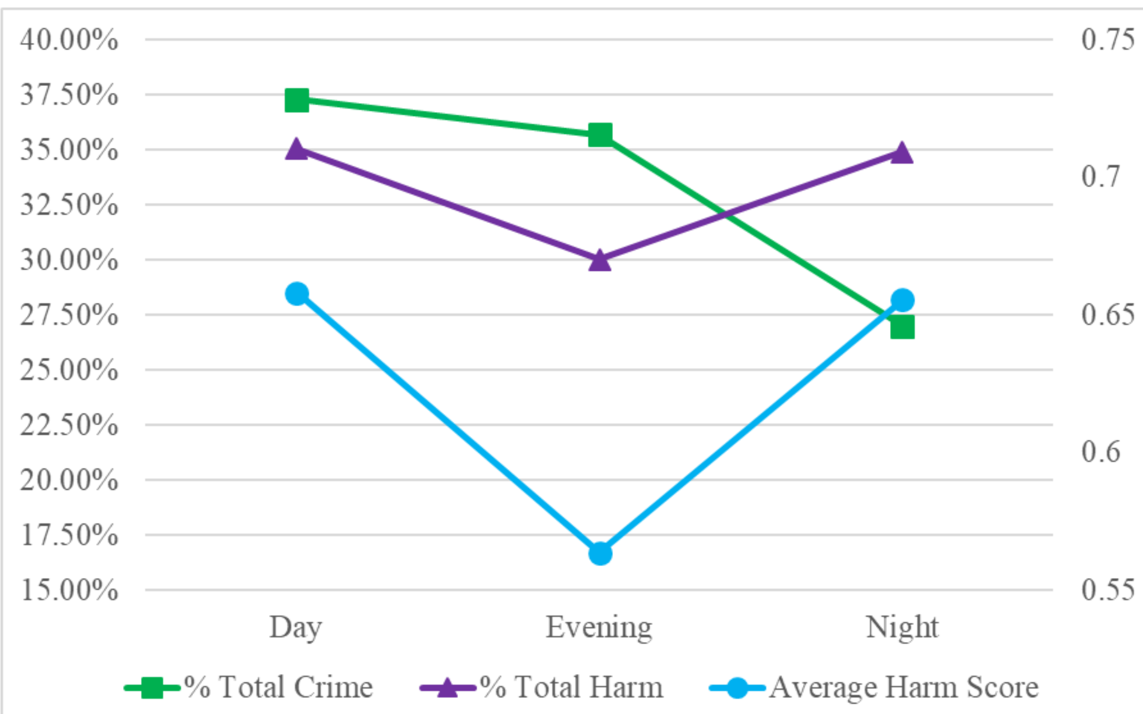


Figure 5.10. Percent of total crime, percent of total harm, and average standardized harm score for all Part I Index Crimes in Austin, Texas, from 2007 to 2017 (by police shift).

Figure 5.10 shows the patterns of the percentages of total crime and total harm, and the average standardized harm scores reported during the different shifts worked by Austin police. Day shift was coded as the hours between 5:45 AM and 3:44 PM, evening between 3:45 PM and 9:59 PM, and night shift from 10:00 PM to 5:44 PM. This was to account for the staggered shift structure followed by APD.

5.6.4 Spatiotemporal Distribution of Harm

The final analysis of Study #2 consisted of examining how the distribution of harm changes over time and space. Figures 5.11 through 5.16 display the results of the spatiotemporal analysis of harm in the city of Austin. Due to the lack of data for the years of 2007 to 2010, and for 2016 and 2017, only the data from 2011 to 2015 were included in this analysis to increase the reliability of these data (N = 139,024). Changes from 2011 to 2013, and then to 2015 were examined using KDE maps, for all Part I Index Crimes reported in those years, resulting in a final sample size of 82,273 Part I Index Crimes for the present analysis.

Over the course of all years of data, the maps are largely consistent from year to year. The city center consistently remains a harm spot from year to year, and the distribution of harm generally follows major roadways in the city. A clear, non-random pattern emerges and persists over the five years included that follows Interstate-35, other major highways, and clusters in the downtown area near 6th Street. However, despite the unweighted crime and the weighted crime being largely concentrated in the same areas, these patterns vary as distance from the highways increase. This finding is inconsistent with the findings in Study #1, in which harm appeared to disperse away from the city center.

When examining the areas near Austin-Bergstrom International Airport on each of these maps, there is evidence that crime and harm are following different social-ecological processes. In the unweighted maps, this area is much "hotter" than the weighted maps, supporting Norton et al.'s (2018) assertion that "…the most harmful harmspots are not made up of just one or two incidents of high harm offenses[(and vice versa)], but a multiplicity of problems and social ailments" (p. 364). In the case of the airport, the opposite is true. There are a large number offenses being reported near the airport that becomes a hot spot in the unweighted maps, which turn out to be low-harm offenses and ultimately do not result in a harm spot in the weighted maps. Similar patterns emerge in the areas further from the major highways.

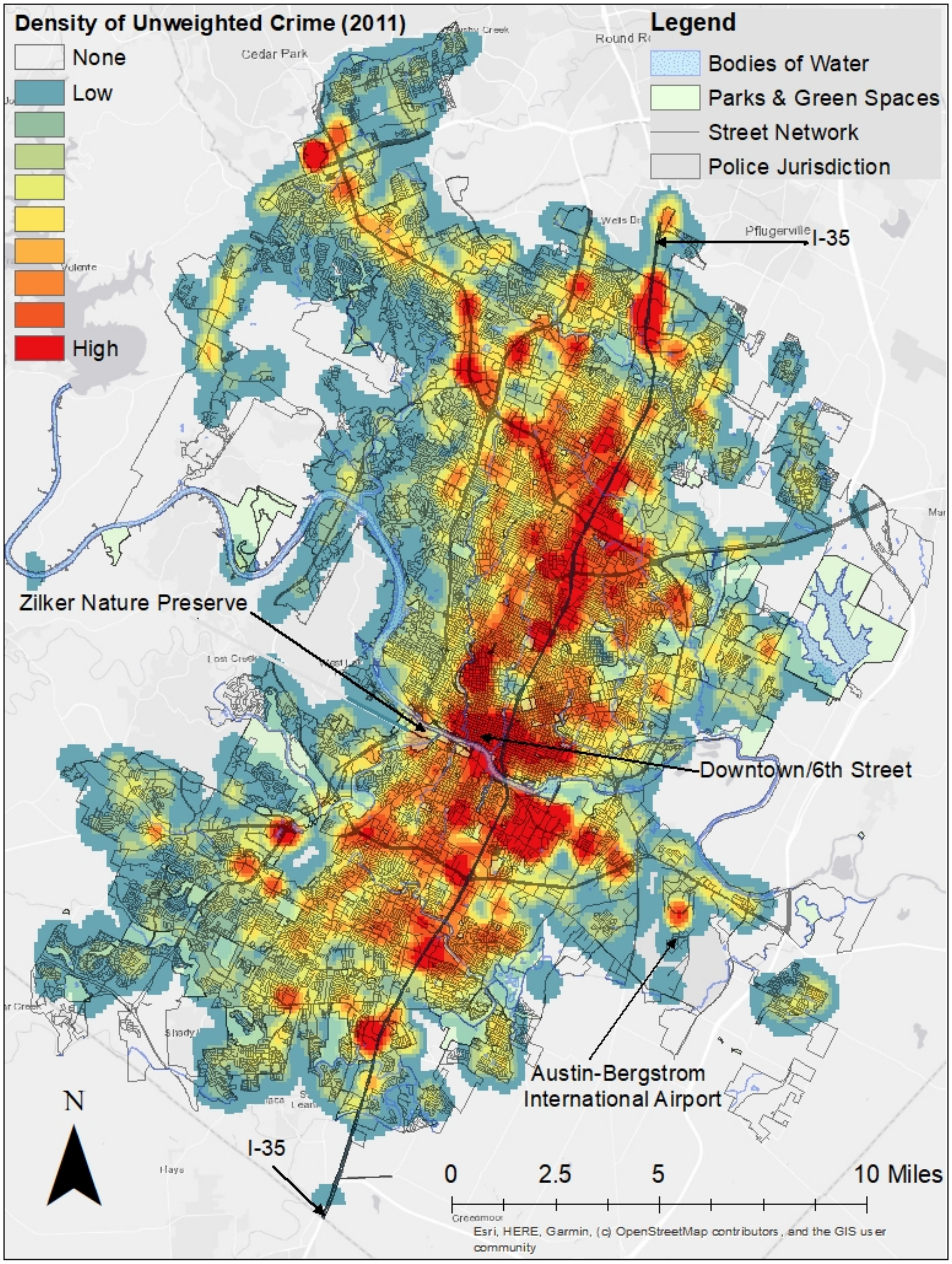


Figure 5.11. Kernel density estimation map of all unweighted Part I Index Crimes in Austin, Texas for 2011.

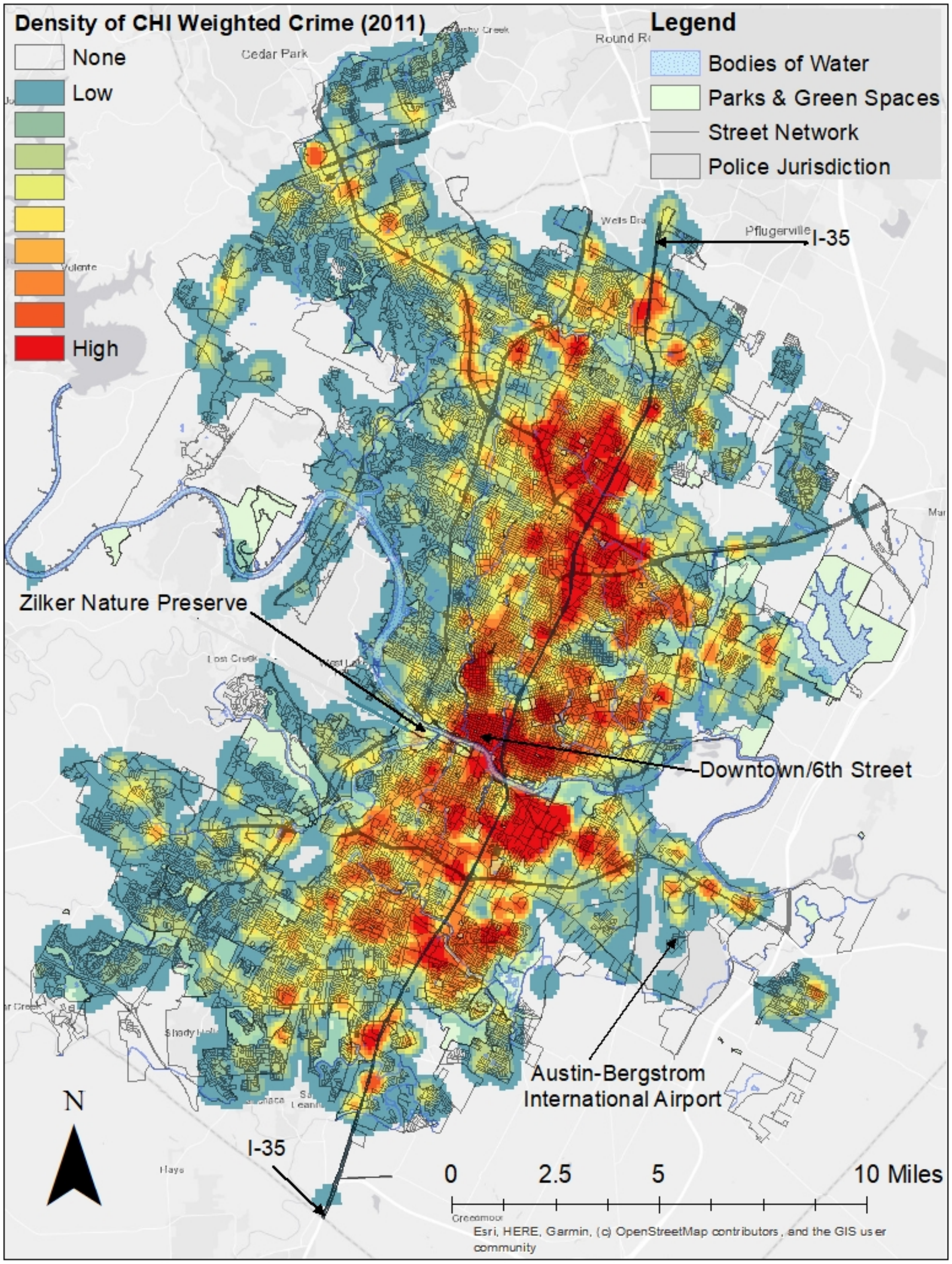


Figure 5.12. Kernel density estimation map of all weighted Part I Index Crimes in Austin, Texas for 2011.

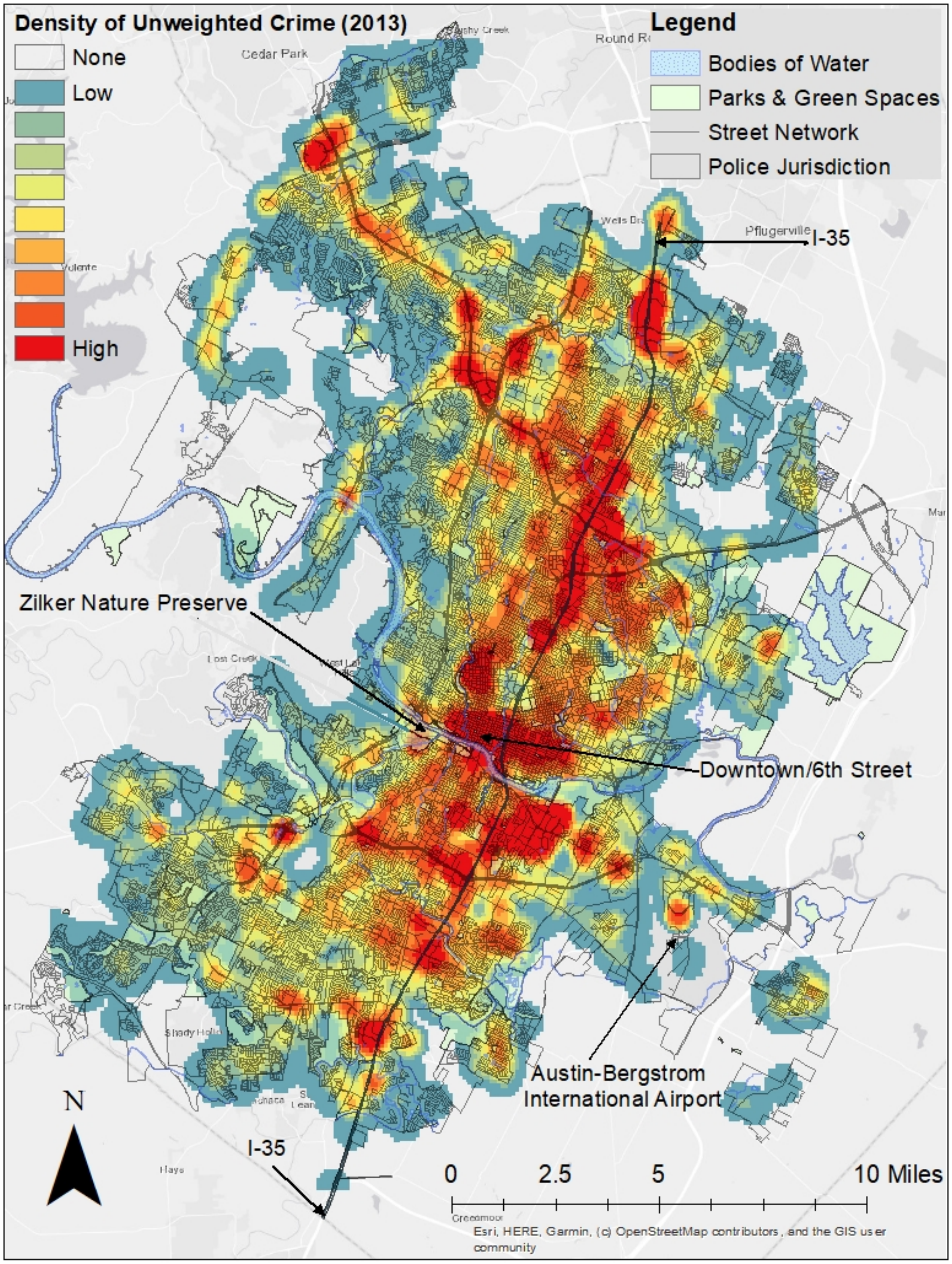


Figure 5.13. Kernel density estimation map of all unweighted Part I Index Crimes in Austin, Texas for 2013.

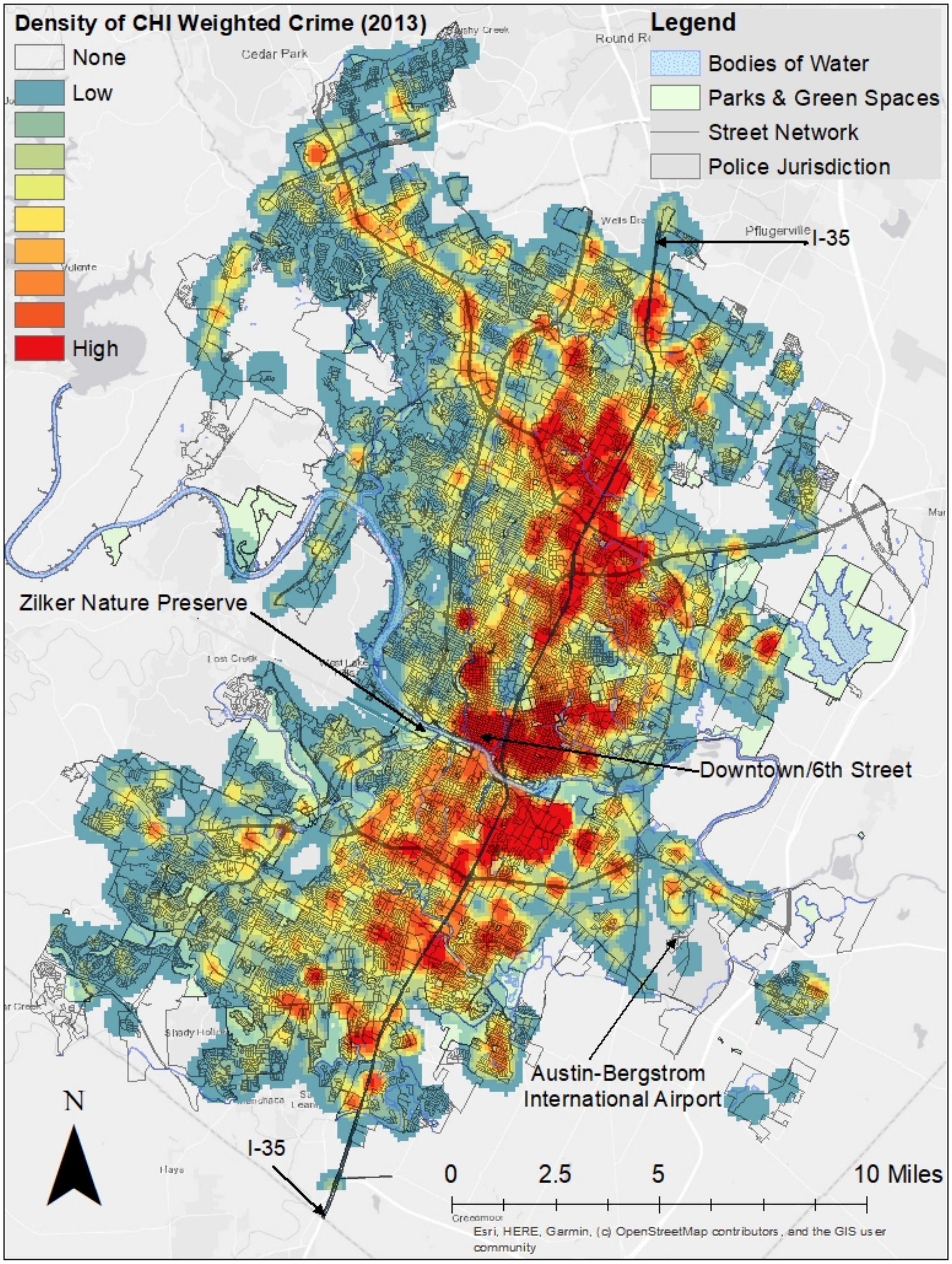


Figure 5.14. Kernel density estimation map of all weighted Part I Index Crimes in Austin, Texas for 2013.

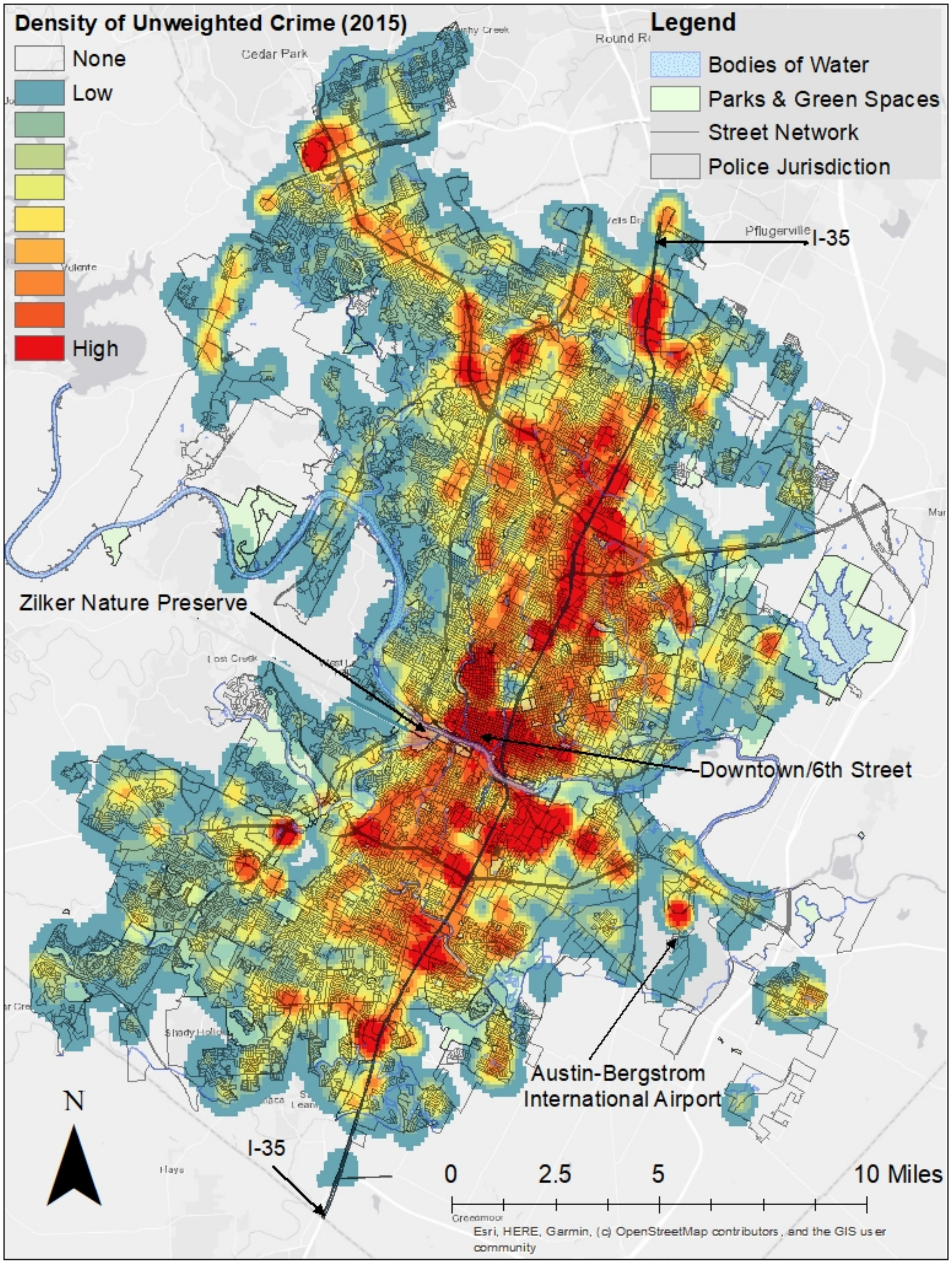


Figure 5.15. Kernel density estimation map of all unweighted Part I Index Crimes in Austin, Texas for 2015.

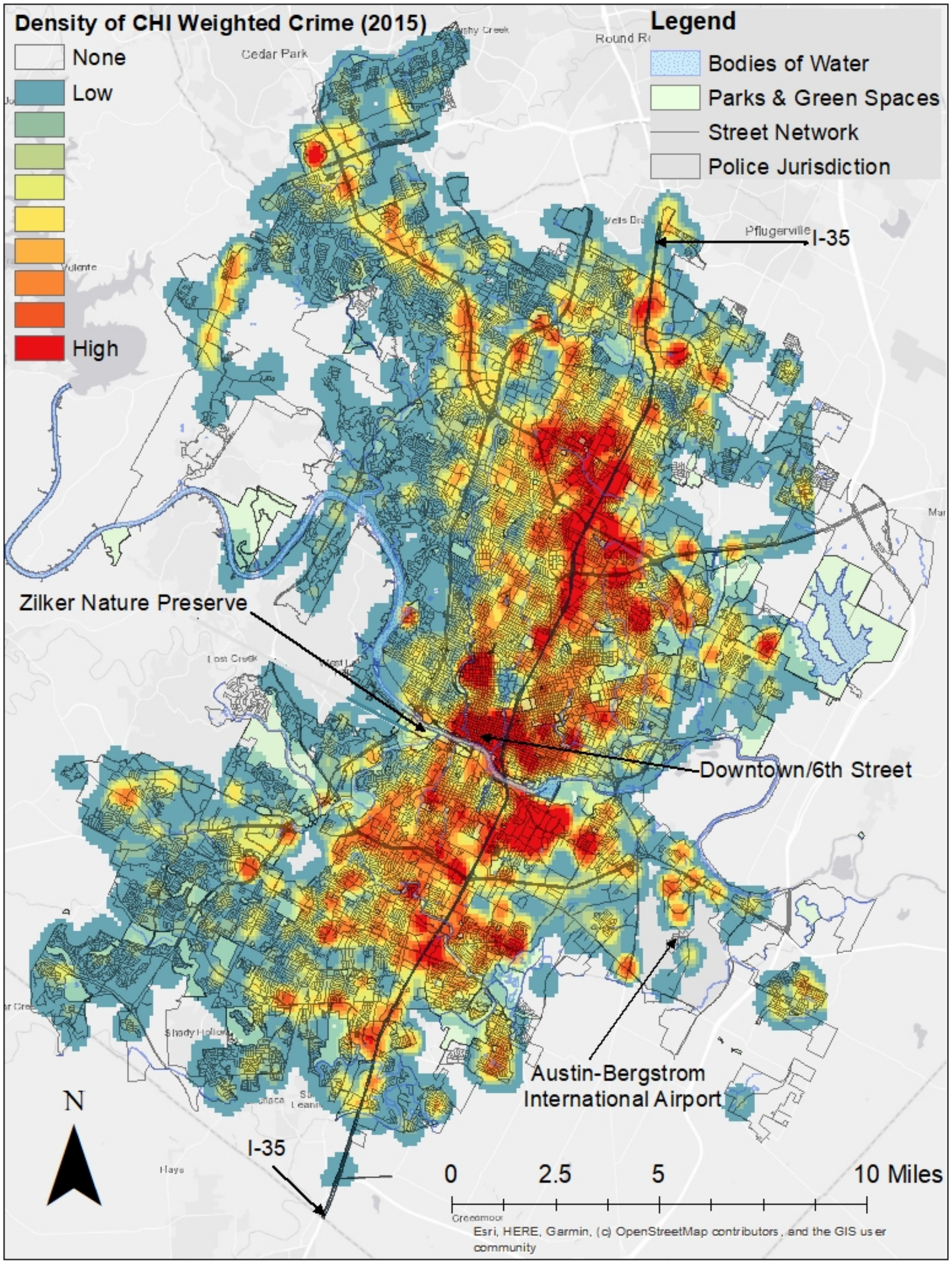


Figure 5.16. Kernel density estimation map of all weighted Part I Index Crimes in Austin, Texas for 2015.

Figure 5.17 shows the spatial concentration of each map in Figures 5.11 to 5.16. Similar to the concentration present in the maps that include all data above, approximately 80% of both crime and harm cluster within approximately 13% of all raster cells. For the weighted crime the number of cells that 80% of harm occurred in increased from 11.78% to 13.51%, and then decreased slightly in 2015 to 13.42% of raster cells. The concentration of raw crime also increased over this same time period. Depending on the locations of where these crimes and harm are spreading, this may be evidence of diffusion effects.

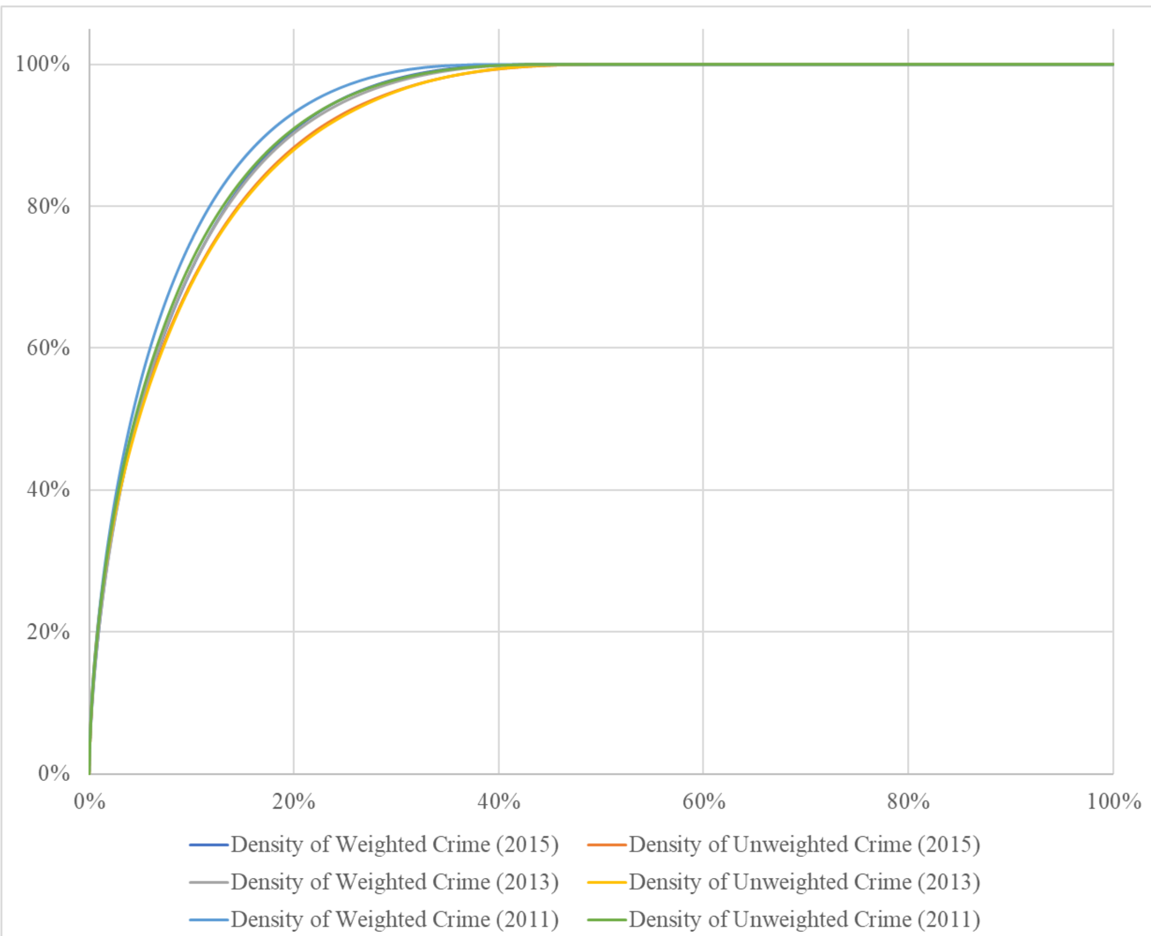


Figure 5.17. Spatial concentration of unweighted and harm-weighted crime, using KDE cell density values as the unit of analysis (number of raster cells varies with year).

5.7 Discussion and Conclusions

The present study addressed three research questions regarding the distribution of harm. The first question asked about the spatial distribution of harm, and whether an observable non-random distribution emerged in the data similar to that reported in Study #1 (Chapter 4). The second question examined the distribution of harm over different periods of time. This is largely based on the work by Norton et al. (2018), while improving on the methodology by including homicides and additional years of data determine if there were noticeable patterns of harm over time. The last question asked if there were observable spatiotemporal patterns of harm, by producing KDE maps and ECDF graphs for both raw and weighted crime over five years.

Study #2 stayed as true as possible to the recommendations and examples provided by Sherman et al. (2016) when weighting the recorded offenses. This is simply due to the fact that the existing tests of the CHI are not consistent and have used different methods to test the viability of harm spot mapping, which is likely the cause of the inconsistent findings in the few studies that have been published to date. In maintaining a similar methodological protocol to Sherman et al.'s (2016) study, Study #2 facilitated more (and better) direct comparisons with previous findings.

Crime counts and crime harm were primarily distributed along the highways and other major roadways. Further from these areas, the patterns became different for crime and harm, and this is observed in the maps that explore these distributions aggregately (all years) and for the time period between 2011 and 2015. The distribution of harm was not more dispersed than the distribution of raw unweighted crime counts, which is inconsistent with the findings from Study #1 (Chapter 4), but the data from Austin were both incomplete (see APPENDIX C – Supplemental Analyses) and had excluded family and domestic violence cases to focus on overt crimes.

Study #1 (Chapter 4) comparing the mapped harm spots identified a crucial issue with using harm scales, and was further observed in the present study. There is a particular relationship between the raw volume of offenses and the appearance of harm spots on a kernel density estimation map that was not addressed in Study #1 (Chapter 4). Specifically, it quickly became apparent in both the maps and the empirical cumulative distribution function graph in Study #1 (Chapter 4) that the raw volume of crime was ultimately still being measured. This prevents researchers from disentangling the concepts of harm and volume, not only simply to map the potentially unique spatial distribution of harm, but also for any research that may require the use of harm weighted offenses. The replication in Study #2, as is, does not offer a suggestion to disentangle this relationship. This of course is problematic, as it is one of the primary criticisms of research that is conducted using harm weighting scales for examining how crime is distributed in space and time.

While the percent of total crime and the percent of total harm tended to produce very similar patterns for each time period examined, each of which are consistent with trends identified in past research (when that particular time period has been examined). However, the average standardized harm scores tended to divert from these patterns and followed a different non-random pattern for most time periods, many of which seemed to invert the trends in the data that only examined the unweighted crime, emphasizing the need to include measures of crime harm when identifying what places and times are most dangerous.

The findings in the present study support the continued need for research that explores how climate and temporal patterns vary from location to location. Many of the temporal findings were consistent with past research, but this should not imply that such findings are generalizable to areas with different climates. While the lack of a truly distinct annual pattern is not clear, this is consistent with previous research (Linning, Andresen, & Brantingham, 2017). The findings in their study indicate that areas with less distinct weather changes are less likely to see any distinct trends in offending over the course of the year.

It is agreeably suggested that disaggregating total crime counts to examine the temporal trends in different crimes types to better understand how climate and environment have an effect on offending. Central Texas offers a generally temperate climate during most months of the year. Following the findings presented by Linning and colleagues (2017; Andresen & Malleson, 2013), the fluctuation of the percentage of total crime from month to month remains largely the same over the course of the year. Further research using ARIMA techniques are likely to result in a similar random pattern as that found in Vancouver (Linning et al., 2917), with the exception of the summer months, in which there are approximately 6 to 8 weeks in which the temperatures are triple digits in Central Texas.

While a large body of literature has focused on the temporal clustering and patterns of crime over different time periods, it seems that little to no focus has been given to the daily fluctuations in crime over the course of a month. Similar to the findings from Linning et al. (2017) and Andresen and Malleson (2013), there may be notable patterns that emerge when crimes types are disaggregated and compared to average pay schedules. Both property and violent crimes may show distinct patterns following estimated pay schedules. For example, on weekends when most people are receiving paychecks, violent crime may spike, as a result of excess social outings involving alcohol. Meanwhile, property crimes may spike toward the end of the pay period, as paychecks begin to run out.

Additional study limitations should also be mentioned. First, the degree of data that is missing from the present study is troubling. However, the aggregate data followed patterns in the percentages of total crime that were consistent with findings from past research, including over the course of the week (Andresen & Malleson, 2015), over the course of the year (Linnings, 2015; Linning et al., 2017), and over the course of the day (Weinborn et al., 2017). While the results should be interpreted with caution due to the amount of missing data, there is still some evidence that, at minimum, the temporal results are reliable. Also, not all crime types were included in these data, which may be affecting the different, but non-random distribution of crime and harm in the city of Austin. In Washington, DC, harm spots occurred in more residential areas, which may contain more family and domestic violence calls than the downtown area of either city. Removing these crimes from the data in Study #2 may explain why

Second, geocoding was inaccurate for only 0.408% of all cases included in these data. However, all sexual assaults included in the data used for the present study. This was done by the City of Austin to protect the privacy of the victims, specifically for those cases that involved children, but the lack of accurate geocoding on sexual assault cases prevented an accurate placement of those offenses on the street network. The most detail that was provided in the data was either a specific block, or an intersection.

The use of an address locator in ArcGIS allowed for an approximate guess for the location at the center of street segments or at the nearest intersection. However, points that were located at an intersection were assigned to a specific segment based on a computer algorithm in which the default selection in a four-way intersection was the last street segment to be added. This maintains consistency on a case by case basis, but it may not be fully accurate when considering how dangerous one street segment is from the next.

Although not necessarily a limitation, the data considered violent and property crime jointly, rather than disaggregating by these larger offense-type categories. There is an argument to be made that there is an objectively different notion of harm associated with both. Ostensibly, things and property are replaceable, despite the hassle associated with having to replace them, while violent crime has implications for physical, psychological, and emotional trauma that is not always easily remedied. This has different implications for both perceptions of crime and fear of crime for residents of specific neighborhoods, as well as for law enforcement that are getting deployed to patrol in certain neighborhoods as well. While it is suggested that it is best to consider the complete circumstances and contributions of harm scores in a neighborhood, it may also help to delineate the difference between violent and property crimes.

In conclusion, the present study presented more evidence to the growing body of literature that is examining how the role of harm changes the way that we measure how dangerous a location is. Simply examining the counts of crime does not provide a complete understanding of what makes a particular location “hot.” The results of the present study indicate that temporal patterns of harm may not follow the established and known temporal patterns of crime counts. Continued research examining the distribution of harm and the use of the CHI (Sherman et al., 2018) are suggested.

6. EXPLORING THE RELATIONSHIP BETWEEN PLACE AND HARM: CONTEXTUAL VARIABILITY OF HARM SPOTS

6.1 Abstract

Recent attention to the use of harm indices to weight crime counts in mapping analysis has led to the development of "harm spot" maps. The existing literature has focused on the spatial and temporal concentration of harm (Study #1, Chapter 4; Study #2, Chapter 5; Norton et al., 2018; Weinborn et al., 2017), and comparing various harm weighting scales (Study #1, Chapter 4). The results of Study #1 (Chapter 4) suggested that harm spots are diffused away from the city center into more residential areas. This implies opportunities for more serious offenses could be higher in residential areas, and that different social ecological processes underlie the spatial distribution of more – versus less – serious crime. In addition, the results of Study #2 (Chapter 5) indicated that both harm and crime followed distinct non-random distributions that were centered around major traffic arteries in Austin, Texas. The social ecological processes observed in Study #1 and Study #2 require further investigation. Study #3 aims to explore the contextual variability of environmental risk factors surrounding harm spots to help understand the processes and correlates that are associated with street segments that have harm scores in the top 33% of summed standardized harm scores.

6.2 Introduction

Research focusing on the spatial clustering of crime has effectively established that crime clusters among offenders and victims and in space and time (Sherman et al., 1989; Weisburd, 2015). In fact, Weisburd (2015) has even codified the law of crime concentration, stating that "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd, 2015, p. 138). Knowing this allowed, and continues to allow, police and other law enforcement agencies to utilize resources in such a way to reduce crime in identified hot spots (Braga, 2005; Braga, Papachristos, & Hureau, 2014).

The question still remains if targeting these high-crime volume areas is the most effective way to reduce the dangerousness of an area. As a response, research examining harm spots developed to provide better evidence of where crime was most serious. Harm spots are simply point addresses, or street segments, where harm clusters, versus a hot spot, which identifies those places where raw crime counts cluster. Research examining harm spots has only recently emerged, although the idea of weighting crime by its relative harm has been described in the literature since as early as the 1960s (Sellin & Wolfgang, 1965). This small body of existing literature has examined the degree of spatial concentration of crime harm (Weinborn et al., 2017); the viability of Sherman et al.'s (2016) Crime Harm Index (CHI) (Study #1, Chapter 4; Study #2, Chapter 5), and the temporal patterns of harm spots over time (Norton et al., 2018; Study #2, Chapter 5).

Crime weighting using the CHI has been tested in New Zealand (Curtis-Ham & Walton, 2017a, 2017b), the United Kingdom (Weinborn et al., 2017), and the United

States (Study #1, Chapter 4; Study #2, Chapter 5). Although Sherman et al. (2016) used sentencing guidelines to create the CHI for the United Kingdom, the index has also been built using actual sentences given to offenders for specific crimes as well (Babyak et al., 2009; Burton et al., 2004). Study #3 uses the U.S. Sentencing Guidelines to create an index following the procedures set out by Sherman et al. (2016) as reported in Study #1 (Chapter 4).

It is known that harm clusters in space, sometimes even more so than crime itself (Study#1, Chapter 4; Weinborn et al., 2017). Currently no research exists that has aimed to explain or predict where harm occurs in the same way that research has explained/predicted places with high crime volume. The present study includes a spatial examination of the distribution of harm in Austin, Texas, in order to identify the effects of crime generators and attractors that contribute to the potential commission of an offense. This is completed through two main analytical techniques: 1) traditional logistic regression models, and 2) conjunctive analysis of case configurations (CACC). The following review of the literature focuses largely on the theoretical framework underlying crime generators and attractors, as it is more focused on the places that are more prone to crime. A full explanation of CACC is also included in the review of the literature as well. A description of the methods is then provided, as well as the analytical strategy. Finally, this chapter concludes with a discussion of the findings and implications for theory, methods, and policy.

6.3 Literature Review

6.3.1 Environmental Criminology

The environmental criminology paradigm also largely relies on the concepts presented by Lawrence Cohen and Marcus Felson (1979) in their seminal paper presenting the routine activity approach to crime, which relies on the intersection of three necessary elements in time and space for a crime to occur. These three elements are a motivated offender, a suitable target, and the lack of a capable guardian. A motivated offender can be anyone, but Cohen and Felson (1979) argue that it is the opportunity structure and the ability to act within that structure that matters to offending behaviors, and that anyone can take the opportunity to act criminally in such situations. As such, motivation is not a primary focus in this research.

A suitable target can be a person or an object. The lack of a guardian indicates that no one is available to keep an eye on the target, or with enough influence to overcome the offenders' motivation and prevent an offense from occurring. Guardians are not limited to being people. For example, there is research that indicates that CCTV cameras also provide a degree of guardianship in certain places to prevent a crime from occurring (Welsh & Farrington, 2009).

Because of both crime pattern theory and routine activity theory, crime can ultimately be a predictable event. Recognizing that there are often commonalities between crime events of a similar nature, and that crime concentrates in time and space, using predictive techniques to identify where problem areas may exist is incredibly important to providing safety and security to residents of a neighborhood or street block. A large body of research dedicated to examining this phenomenon has been published in the last 30 years to better understand how where and when crime is most likely to occur. These places where crime clusters and the times that crime occurs more frequently are known as crime hot spots.

6.3.2 Hot Spots Mapping

Research on hot spots mapping originated in a study in Minneapolis by Sherman, Gartin, and Buerger (1989), in which they examined the spatial distribution of police calls for service. Sherman et al. (1989) reported that 50% of 323,979 police calls for service in Minneapolis over a 12-month period were concentrated in 3% of addresses. Since then, research has supported this finding demonstrating that crime cluster in both space and time. This more contemporary line of research is generally based on the assumptions that crime has an inherent geographical quality in that it has to occur at a specific place (Chainey & Ratcliffe, 2005; Chainey, Tompson, & Uhlig, 2008), and that crimes are a result of an interaction between an offender and a victim at these particular places (Brantingham & Brantingham, 1993; 1995; Chainey et al., 2008; Cohen & Felson, 1979).

Hot spots mapping has since "become a popular analytical technique used…to visually identify where crime tends to be highest" (Chainey et al., 2008, p. 5), and is used to deploy resources. However, the primary argument for Study #1, Study #2, and the present study is that simply examining crime volume only provides a partial understanding what makes a place a hot spot, or a more dangerous place. As such, the first two studies in this dissertation have focused on comparing the distribution of crime volume to crimes that are weighted by their relative harm to better understand what makes a place dangerous. The next logical step, following the hot spots literature, is to investigate ways to predict harm spots based on environmental risk factors.

6.3.3 Harm Spots

Research has further tried to understand the distribution of crime by adding a third dimension to hot spots research. This new research focuses on providing a more nuanced approach to hot spots policing strategies that allows law enforcement to see where more serious crimes are being committed. In this vein, Norton et al.'s (2018) supplemental analyses indicated the presence of risky facilities at temporally significant harm spots, such as bars, pubs, and night life venues, as alcohol can often be a contributing factor to crime and violence. Research examining the environmental risk factors that contribute to high-harm versus low-harm harm spots has been limited to a single study (Norton et al., 2018). Therefore, Study #3 is largely exploratory. Having said this, it is informed by past research that has examined crime-specific risk factors. For example, much of the existing research examining risky facilities examines the relationship between these facilities and robberies (Barnum et al., 2017; Bernasco & Block, 2011; Hart & Miethe, 2014; Summers & Caballero, 2017).This research provides a place to start in detecting which environmental factors contribute to high-harm and low-harm harm spots.

6.4 The Current Study

Most of the existing research on harm spots has provided empirical evidence of the viability of weighting crime by a relative harm score and the resulting effect that this has on geospatial examinations of harm (for example, Ignatans & Pease, 2016; Ratcliffe, 2015; Sherman, et al., 2016). Additional research has investigated which weighting scheme is best, although the evidence does not strongly support one over the other

(Sherman et al., 2016). What is becoming more obvious is that harm follows different and distinct spatial and temporal patterns compared to crime volume, and, as such, the purpose of Study #3 is to examine the contextual variability in harm spots of varying intensity.

Contextual variability does not necessarily provide a causal explanation of the unique spatial distributions of harm, but it does provide a steppingstone in that direction. There are, of course, several theoretical frameworks that may potentially contribute to understanding these unique distributions, but Study #3 focuses solely on environmental explanations, including those related to crime attractors and generators and routine activity theory. Therefore, the primary research question in Study #3 is as follows: is there a discernable context for high-harm versus low-harm places? Study #3 seeks to answer this question by using facilities data to examine to which extent their presence influences the spatial distribution of crime harm.

6.5 Methods

6.5.1 Data Sources

The data for Study #3 were collected or compiled from several sources. First, the purpose of Study #3 is to examine the environmental context of harm. Therefore, this study requires access and use of geocoded facilities data to determine the unique configuration of facilities that are collocated with high-harm and low-harm harm spots. Publicly available geocoded facilities data collected and maintained by referenceUSA (http://resource.referenceusa.com/available-databases/) were used for the present study.

The facilities are supported by previous research, which subsequently serves as justification for their use as a starting point to explore how context affects the relative harm of a street segment (see, for example[2], Barnum et al., 2017; Bernasco & Block, 2011; Franklin, LaVeist, Webster, & Pan, 2010; Groff & Lockwood, 2014; Hart & Miethe, 2014; Kooi, 2013; LeBeau, 2012; Lersch, 2017; Murray & Swatt, 2013; Summers & Caballero, 2017; Toomey, Erickson, Carlin, Lenk, Quick, Jones, & Harwood, 2012) and include ATMs, convenience stores, drinking establishments, fast food restaurants, gas stations, lodging locations, liquor stores, banks and other financial institutions, pharmacies, police department locations, schools, and smoke shops. Based on the exploratory nature of Study #3, facilities that are not often considered as risk factors, but have potential effects on crime rates, have also been included (e.g., banks and other financial institutions, pharmacies, and police departments). The results of the present analysis are meant to serve as a stepping stone to better understand how contextual variability affects the presence of harm spots, and as such future studies may explore the effects of facilities that have not been regularly considered in the existing literature.

Geocoded crime data recorded in Austin, Texas, are used in the present study. These data include the address, geographic coordinates, date, and time of every offense reported to the Austin Police Department (APD) between the years of 2011 and 2015 (N=139,024 offenses). Table 6.1 displays the distribution of crimes for all Part I Index Crimes that occurred in Austin from 2011 to 2015, inclusively. The eight crime types included in Study #3 are all UCR Part I Index Crimes, namely aggravated assault, arson,

[2] Each of the studies listed as an example uses at least one of the facilities included in this analysis, although they only examine the effect these facilities have on one crime type. Barnum et al., (2017), Bernasco and Block (2011), Hart and Miethe (2014), and Summers and Caballero (2017), examined robberies; Lersch (2017) examined car jackings; Franklin et al. (2010) and Toomey et al. (2012) examined violent crimes; Groff and Lockwood (2014), Kooi (2013), and LeBeau (2013) examined a variety of unweighted crime events; Murray and Swatt (2013) examined residential burglaries, motor vehicle theft, and felonious assault.

burglary, homicide, larceny-theft, motor vehicle theft, rape, and robbery. Additionally, no cases in which domestic and family violence was cited were included in the data.

Table 6.1. Number and percentage of offenses between 2011 and 2015 (inclusive) in Austin, Texas, and corresponding raw and standardized crime weights for the CHIUS crime seriousness scales, by crime type.

	Recorded crime		CHI_{US} scores[a]	
	N	%	Raw	Std.
Property Offenses				
Arson	430	0.31	1,230	11.39
Burglary	18,464	13.28	495	4.58
Larceny-Theft	105,662	76.00	30	0.28
Motor Vehicle Theft	6,545	4.71	810	7.50
Violent Offenses				
Aggravated Assault	4,665	3.36	720	6.67
Homicide	81	0.06	10,800	100.00
Rape	274	0.20	2,910	26.94
Robbery	2,903	2.09	1,380	12.78
Total	139,024	100.00	27,176,970	251,833.13

[a] Scores were calculated using the U.S. Sentencing Guidelines (see Appendix 3).

In addition to crime data, businesses and facilities data were collected to measure the effect of crime generators and attractors on the presence of high-harm harm spots. A total of 2,770 facilities were examined for their effect on harm. Table 6.2 displays the frequencies of each facility type that was included in these analyses. The facilities present a minor limitation; these data were collected in 2017 and may introduce a time order issue with the analyses for the present study. Because referenceUSA keeps up-to-date geocoded business data, the facilities that were present in 2017 may not have been in 2011 and vice versa.

Table 6.2. Facility types and the frequencies of each type (Austin, Texas, 2017, referenceUSA).

Facility Type		N	%
ATMs		727	26.25
Banks, Credit Unions, and Other Financial Institutions		364	13.14
Banks	242		
Check Cashing Services	10		
Credit Unions	75		
Money Transfer Service	10		
Other Financial Institutions	95		
Convenience Stores		187	6.75
Alcohol Establishments		200	7.22
Bars	139		
Cocktail Lounge	25		
Comedy Clubs	3		
Night Clubs	24		
Pubs	4		
Other	5		
Fast Food Restaurants		139	5.02
Gas Stations/Service Station		184	6.64
Law Enforcement Agency Building Locations		23	0.83
Liquor Stores		110	3.97
Hotels and Other Lodging		247	8.92
Pharmacies		169	6.10
Schools		363	13.10
Smoke Shops		57	2.06
Total		2,770	100.00

For the dependent variable in the present study, the unit of analysis was the street segment. Following the logic of Weisburd, Bushway, Lum, and Yang (2004), a street segment has a significant relevance in organizing urban life. Austin, Texas has a population over 750,000 and therefore meets the United States Census Bureau's definition of an urban area. Street segments, also called street blocks or face blocks, is the length of street between two intersections (Weisburd, Bushway, Lum, & Yang, 2004). In these analyses, the sample size is then based on the total number of street segments in the map in the APD jurisdiction (N=34,138).

6.5.2. CHI Weighting Scale

Research has shown that there is general agreement that violent crimes are more severe, or harmful, than property crimes (Adriaenssen et al., 2018; Blum-West, 1985; Stylianou, 2003). This was reflected in the sentencing recommendations at the federal level in Study #1 (Chapter 4) and Study #2 (Chapter 5). Although crime is generally a result of local policy and practice more so than the result of national law, the CHI methodology will be constructed using the U.S. Sentencing Guidelines (2016) to ensure that the harm scores are consistent between the studies.

The CHI has not been consistently constructed from jurisdiction to jurisdiction in the few places that it has been implemented. Study #1 (Chapter 4) and #2 (Chapter 5) closely followed the original description of the CHI methodology (Sherman et al., 2016), using broad UCR Part I Index Crime offense categories and the native country's sentencing guidelines. However, this is not the only method that has been used to construct the CHI. In New Zealand, Curtis-Ham and Walton (2017a, 2017b) utilized existing official sentencing data to weight calls for service and included all offenses listed, not just the broad categories that had been used in Sherman et al.'s (2016) original research. Therefore, scores are not fully comparable as they have not been calculated consistently using the same, or similar, sources for the harm calculations. However, the Cambridge CHI displayed a significant degree of similarity (Study #1, Chapter 4 and Study #2, Chapter 5) to the CHI constructed using the U.S. Sentencing Guidelines, which indicates that these scales are performing in a similar way.

6.5.3 Data Cleaning: Geocoding, Spatial Joins, and Missing Data

The total number of cases that occurred between the years of 2007 and 2017 was 542,882. From this population, all cases including family and domestic violence were eliminated, as were any cases in which the highest offense recorded was not a UCR Part I Index Crime. These offenses are generally those that are annually submitted to the Federal Bureau of Investigation's Uniform Crime Reports, and were also those offense categories used in Study #1. This resulted in the total number of cases reported in Table 5.1 (N=145,571). These data were further parsed to increase the reliability of the results by using all Part I Index Offenses that occurred between 2011 and 2017, which are reported in Table 6.1 (N=139,024).

To conduct regression and conjunctive analyses, the crime event and facilities point data had to be spatially joined to the street segment base map (created by the City of Austin and made available for public use by the Austin Open Data Portal, which is maintained by the city). The join was performed in several steps in order to format the data tables associated with the spatial data in a way that would be useful for analysis in programs that are external to ArcMap 10.6. Street segments were spatially joined to the crime event points (lines to points) in order to have a street segment associated with each point in the data. Spatial joins are not exact; rather, these joins are based on algorithms built into the GIS software which selects the street segment that is the smallest distance from that point. To prevent a point from joining to multiple streets, the reverse operation was conducted to ensure that each point had a street segment associated with it. No minimum distances were specified for this operation.

Another variable is generated automatically in the data attribute table that indicates the point's actual distance from the street segment in feet to control for this disparity, if necessary. In the spatial join between crime events and the closest street segment, the largest distance was approximately 2,780 feet. All the crime event points at this distance are associated with crimes that occurred in St. Edwards Park in northwest Austin, which likely contributes to the distance from the closest street segment.

Following this step, street segments were spatially joined to separate layers for each facility type using the same process. The final table was generated by merging both the facility data and the crime event data with the street segment table, which allowed for individual variables to be created with the counts of crime and facility type by street segment, as well as summed unweighted crime counts and the summed standardized harm score for each street segment. These variables were then used to create the outcome measure

6.5.4 Analytical Strategy

Study #3 involved a series of phases. The first phase includes describing the sample, using univariate statistical techniques. This is followed by a series of model estimations using different statistical techniques that have all been employed in previous research to identify contextual trends in environmental risk factors around hot spots (for example, Aniyam, 2015; Dugato, 2013; Franklin et al., 2010; Hart & Miethe, 2014; Kooi, 2013; Lockwood, 2007; Summers & Caballero, 2017). Study #3 extends these techniques to explore the contextual variability surrounding harm spots and includes the following model estimation techniques: 1) conjunctive analysis of case configurations, and 2) traditional binary logistic regression models. Each of these is described in greater detail below.

The present study estimated two binary logistic regression models. The dependent variable is a measure of whether a street segment has a harm score that is in the top third of the distribution of harm scores for all eleven years of data (1 = yes). This variable was dichotomized into high-harm street segments, versus all other harm street segments (middle range, and low), in which 1 was equal to a street segment having a harm score in the top 33% of the distribution. The independent variables included all the crime generator and crime attractor variables described above. The first model estimates the effect of the number of independent facility types on the presence of a harm spot on a street segment. In other words, the total count of facilities by type was utilized as the independent variable. The second model estimates the effect of the presence of any number of independent facility types on the presence of a harm spot on a street segment.

6.5.4a Binary Logistic Regression

In social sciences, the notion of cause and effect becomes clouded due to a lack of true experimental design. For this reason, we must rely on inferential statistics and strong theoretical foundations to understand cause and effect in a way that approximates a true experimental design. Therefore, when conducting a study, we impose causality on mathematical models to better understand how social concepts interact with one another in a causal relationship. In its simplest form, a regression equation is meant to measure the effect that an independent variable has on the dependent variable. This differs from a correlation in that we have forced the computer to recognize that there is a causal relationship present. A correlation coefficient is simply just a measure of how two variables change together, and therefore only provides the strength and direction of the relationship. Regression coefficients are interpreted in terms of manipulating the independent variable to see what the dependent variable does in response. The effect, then, can be equated to the slope in the more familiar algebraic equation of $y = mx + b$.

Study #3 utilizes binary logistic regression as the outcome variable is dichotomous. Binary logistic regression is a logit transformation of the generalized linear model, in which a logit is the logged ratio of probabilities that an event will occur. In social sciences, this is the probability that a case belongs in the group of interest. This category of interest in the Study #3 is high-harm harm spots. The resulting coefficients from an estimated binary logistic model are reported in the logged odds, but this is ultimately a difficult interpretation of the relationship between X and Y. The logged odds can be converted into simple odds by exponentiating the effect. These simple odds, or Odds Ratios, provide an interpretation that indicates a factor change in the odds of a case belonging in the category of interest.

6.5.4b Conjunctive Analysis of Case Configurations

Conjunctive analysis of case configurations (CACC) is an extension of exploratory data analysis and has only recently been introduced to criminological research (Miethe et al., 2008), although it is analogous to an older technique developed by Ragin (1987) known as qualitative comparative analysis (QCA). To further explain the mechanics of QCA, Miethe et al. (2008) state that "QCA is designed to bridge the gap between case-oriented qualitative research and variable-oriented quantitative studies…as complex configurations of elements…[assumes] there are multiple causes of the same outcome" (Miethe et al., 2008, p. 228). Both techniques emphasize that there is a unique combination of features that is likely to explain a particular outcome, which may get obscured in a regression model in which complex interactive effects are not possible to calculate (Miethe et al., 2008; Ragin, 1987).

The methods for CACC draw from statistical techniques used for discrete multivariate analyses, but simply provide a way to model causal relationships and complex interactions using categorical variables (Miethe et al., 2008). This technique has been applied to many criminological outcomes including self-defensive gun use, intimate partner violence, providing environmental context to urban crime, and understanding contextual variation in violent offending behaviors using biopsychosocial predictors (for example, see Fenimore & Jennings, 2018; Hart, 2014; Summers & Caballero, 2017). For all that context matters in criminological and criminal justice research, CACC provides the ability to examine how the context varies even for crime and justice outcomes (Hart, 2014), and can be "used to understand the complex causal relationships that emerge when combinations of variables are present or absent" (Hart, 2014, n.p.) even when the desired outcome remains constant.

CACC consists of a simple three-step process (Hart, 2014; Hart, Miethe, & Regoeczi, 2014; Miethe et al., 2008). In the first step, a truth table is created, which consists of all possible combinations of explanatory (independent) variables. The total number of combinations requires an exponential calculation. Therefore, eight explanatory variables that are coded with a simple presence or absence of a particular characteristic or trait results in 256 total possible combinations of independent variables (where 2 categories raised to 8 independent variables is equal to 256 possible combinations, or $2^8 = 256$). There is a possibility of including independent variables with more than one category (e.g., an age variable divided into quartiles), which will simply change the equation to $2^7 \times 4^1 = 512$. In the truth table, each row represents each of the theoretically possible unique configurations of the explanatory variables included in the model.

No limit has been identified for the number of case configurations (combinations of independent variables), although a high number of possible case configurations can be problematic with small sample sizes. This is akin to low cell counts in a Chi-square analysis in that the reliability of the measures decrease when cell counts are too low. The total of unique configurations is often less than 100 in order to prevent this from becoming problematic during an analysis (Miethe et al., 2008).

The second step in CACC is to populate the table with the data. Specifically, this means that the data are sorted. The number of times each unique case configuration is observed is reported as a count in the truth table. The third step requires applying decision rules for defining dominant case configurations to prepare the data for analysis. This results in another table that consists of only the dominant case configurations. Dominant case configurations are defined by the rule of thumb that those with fewer than 5 observations are considered rare, and this rule should be applied to samples that are smaller than 1,000. If the sample is larger than 1,000, those configurations with less than 10 observations are considered rare (Hart, 2014; Miethe et al., 2008). Miethe et al. (2008) suggest that removing case configurations with less than 5 or 10 observations ensures that more substantive conclusions can be drawn from the dominant case configurations. Eliminating configurations that have fewer than the number of observations recommended based on sample size prohibits estimating fully saturated models, but does allow for estimating more stable net effects (Miethe et al., 2008). This can be likened to the rules of thumb for the minimum number of cases per cell in Chi-square analyses.

This phase of the analysis includes exploring if there is any clustering within the dominant case configurations established in the third step of the analysis, as well as examining the relative frequencies. As is the case in most criminological research, one should expect that the majority of observations should cluster in very few unique case configurations, although this is not always the case (see Fenimore & Jennings, 2018). An examination of the dominant case configurations will allow an evaluation of the most common context for the desired outcome. In the case of Study #3, this means that this step will include identifying the most common case configuration for both high-harm and low-harm harm spots. For example, this will include reporting the presence or absence of particular environmental characteristics, such as the presence of liquor establishments or a public school. This cases the unit of analysis to change to each unique case configuration.

The quantitative component of CACC is included in the final phase of analysis. This includes examining the relative differences of risk of a harm spot. Risk profiles are compared to determine the relative importance of each variable by looking at common risk factors within three separate groups observed in the data: 1) those with greater than the overall mean risk of the desired outcome; 2) those with substantially lower risk (more than one standard deviation below the mean); and 3) those that fall between these two groups (Miethe et al., 2008). Those groups can be evaluated for what is found to be in common for observations that fall within each of the groups. In order to calculate the relative differences of risk, the relative risk of the unique configuration without the characteristic of interest is subtracted from the relative risk of the unique configuration with the characteristic of interest. The resulting risk difference can be reported as either a negative or positive risk difference.

In this step, it is also possible to examine the interactions between all of the included explanatory variables. For example, if five explanatory variables were included in the model, there is a possibility that a five-way interaction can be reported in the data, which is an obvious drawback of traditional regression models, which are not really equipped to handle such a complex interaction term.

6.6 Results

6.6.1 Binary Logistic Regression Results

Table 6.3 displays the results of the first binary logistic regression model explaining the presence of harm spots with scores in the top 33% at the street segment level using the counts of the facilities as independent variables. The likelihood ratio test (LRT) is a model-level test that compares the difference between the restricted and unrestricted model. The null hypothesis of the LRT is that all slopes in the model are equal to 0 in the population, while the alternative hypothesis states that *at least one slope* in the model is not equal to 0 in the population. The model Chi-square is the difference between the restricted model's -2 log likelihood and the unrestricted model's -2 log likelihood, and is equal to 1236.922, which lies in the critical region. Therefore, one would reject the null hypothesis and conclude at the 0.05 level of statistical significance that the unrestricted binary logistic regression model is a better fit for the data than the restricted model. The analysis should proceed with the theoretical model from Table 6.3.

Table 6.3. Logistic regression model testing the log odds of a harm spot with a harm score in the top third of the distribution using counts of facility type as the independent variable (n=34,138).

Variable	b	SE	Wald	OR
Constant	-1.801*	0.016	12,929.758	0.165
ATMs	1.101*	0.095	134.519	3.007
Convenience Stores	1.309*	0.176	55.147	3.703
Drinking Establishments	1.402*	0.168	69.997	4.065
Fast Food Restaurants	0.750*	0.207	13.184	2.118
Banks and Financial Institutions	0.451*	0.118	14.726	1.570
Gas Stations	1.213*	0.167	52.953	3.363
Liquor Stores and Liquor Retail	1.193*	0.224	28.368	3.298
Hotel and Lodging	1.712*	0.149	132.200	5.538
Pharmacies	0.618*	0.174	12.654	1.855
Law Enforcement Agencies	0.615	0.552	1.242	1.849
Schools	0.717*	0.106	46.174	2.049
Smoke Shops	1.646*	0.316	27.196	5.186
-2LL: 28,199.463	Nagelkerke R^2: 0.062		Goodness of fit:	χ^2 = 1,236.922*

DEPENDENT VARIABLE: presence of harm spot (harm score in the top 33% = 1)

* $p < 0.05$

ABBREVIATIONS: SE = standard error; OR = Odds Ratio/Simple Odds

The effects of the independent variables on the dependent variable are interpreted as the change in the logged odds of the presence of a harm spot when the independent variable increases by one count. The corresponding Wald statistic indicates whether the coefficient exceeds a standardized value associated with statistical significance. All facility types, except law enforcement agencies, were significant risk factors for the presence of a high harm spot on a street segment. In this model, the addition of one lodging facility increases the odds of a harm spot by 454%, one additional smoke shop increases the odds by 419%, and one additional drinking establishment increases the odds by approximately 300%.

Table 6.4 Logistic regression model testing the log odds of a harm spot with a harm score in the top third of the distribution using presence/absence of facility type as the independent variable (n=34,138).

Variable	b	SE	Wald	OR
Constant	-1.807*	0.016	12923.120	0.164
ATMs	1.266*	0.105	146.714	3.546
Convenience Stores	1.362*	0.184	55.059	3.905
Drinking Establishments	1.777*	0.197	81.806	5.914
Fast Food Restaurants	0.704*	0.216	11.693	2.096
Banks and Financial Institutions	0.611*	0.144	17.928	1.843
Gas Stations	1.485*	0.192	60.026	4.416
Liquor Stores and Liquor Retail	1.227*	0.244	25.206	3.412
Hotel and Lodging	2.077*	0.163	163.257	7.984
Pharmacies	0.834*	0.194	18.553	2.302
Law Enforcement Agencies	0.750	0.521	2.072	2.116
Schools	0.858*	0.128	45.028	2.359
Smoke Shops	1.663*	0.314	27.991	5.273
-2LL: 28,172.481	Nagelkerke R^2: 0.063		Goodness of fit: χ^2 = 1,263.904*	

DEPENDENT VARIABLE: presence of harm spot (harm score in the top 33% = 1)

* *$p < 0.05$*

ABBREVIATIONS: SE = standard error; OR = Odds Ratio/Simple Odds

The second regression model looked specifically at how the presence or absence of these crime generators and attractors affect the probability of a street segment having a high harm. Table 6.4 displays the results of this analysis. Again, the model level Chi-square value was found to be significant, therefore, proceeding the analysis with this unrestricted model is suggested. The results again indicate that the presence of all crime generators or attractors have a significant effect on the likelihood of a high-harm harm spot, with the exception of law enforcement agencies. The first binary logistic regression model found that lodging facilities, smoke shops, and drinking facilities had the highest odds of a harm spot being present.

In the present model, these same variables result in the largest factor change in the odds. Street segments with at least one hotel or other lodging facility had nearly 700%

higher odds of having a high harm score than streets without these facilities present. Those street segments with at least one drinking establishment had a 490% higher probability of having a high harm score compared to those without these facilities present. The street segments with at least one smoke shop had approximately 420% high odds than those without.

6.6.2 Conjunctive Analysis of Case Configurations Results

The results of the CACC are presented in Table 6.5 and Table 6.6 in such a way that one can see what configurations result in street segment with high harm scores. Table 6.5 is ordered by the number of cases per configuration, and Table 6.6 is ordered by the relative risk differences from largest to smallest, which allow the reader to visualize the patterns of clustering and variability among the case configurations in an easily observable manner. The total number of possible case configurations was 4,096 (2^12). However, only 160 total configurations were observed in the data. This number was further reduced when applying the rules of dominant case configuration (N > 10 observations) (Miethe et al., 2008), resulting in a total 23 dominant case configurations used for the analysis. This allows for more stable net effects, despite the fact that eliminating lower frequency cells prohibits estimating a fully-saturated model (Miethe et al., 2008).

When examining Table 6.3, there is observable clustering within the number of cases, as well as a significant degree of variability between the most common and least common configurations (N=33,276 and N = 10, respectively). In the top five most common configurations, the presence of only one facility type being present at a time was

Table 6.5 Case configurations of high-harm street segments ranked by cases per configuration.

Configuration	ATMs	Convenience Stores	Drinking Establishments	Fast Food Restaurant	Financial Institutions	Gas Stations	Liquor Stores	Hotels and Lodging	Pharmacies	Law Enforcement Agencies	Schools	Smoke Shops	Relative Risk	Number of Street Segments
1	0	0	0	0	0	0	0	0	0	0	0	0	0.14	32528
2	0	0	0	0	0	0	0	0	0	0	1	0	0.30	270
3	1	0	0	0	0	0	0	0	0	0	0	0	0.54	200
4	0	0	0	0	0	0	0	1	0	0	0	0	0.62	121
5	0	0	0	0	1	0	0	0	0	0	0	0	0.38	121
6	1	0	0	0	1	0	0	0	0	0	0	0	0.51	71
7	0	0	0	0	0	0	0	0	1	0	0	0	0.43	69
8	0	0	1	0	0	0	0	0	0	0	0	0	0.63	64
9	0	0	0	0	0	1	0	0	0	0	0	0	0.68	63
10	1	1	0	0	0	0	0	0	0	0	0	0	0.63	63
11	0	1	0	0	0	0	0	0	0	0	0	0	0.63	56
12	0	0	0	1	0	0	0	0	0	0	0	0	0.47	45
13	1	0	0	0	0	1	0	0	0	0	0	0	0.66	41
14	0	0	0	0	0	0	1	0	0	0	0	0	0.61	36
15	1	0	0	0	0	0	0	1	0	0	0	0	0.66	29
16	0	0	0	0	0	0	0	0	0	0	0	1	0.67	27
17	1	0	1	0	0	0	0	0	0	0	0	0	0.83	23
18	1	0	0	0	0	0	0	0	1	0	0	0	0.73	15
19	0	0	0	0	0	0	0	0	0	1	0	0	0.36	14
20	1	0	0	0	1	0	0	0	1	0	0	0	0.73	11
21	1	1	0	0	0	1	0	0	0	0	0	0	0.55	11
22	1	0	0	0	0	0	1	0	0	0	0	0	0.70	10
23	1	0	0	1	0	0	0	0	0	0	0	0	0.60	10

Table 6.6 Case configurations of high-harm street segments ranked by relative risk difference.

Configuration	ATMs	Convenience Stores	Drinking Establishments	Fast Food Restaurant	Financial Institutions	Gas Stations	Liquor Stores	Hotels and Lodging	Pharmacies	Law Enforcement Agencies	Schools	Smoke Shops	Relative Risk	Number of facilities on segment	Number of Street Segments
1	1	0	1	0	0	0	0	0	0	0	0	0	0.83	2	23
2	1	0	0	0	0	0	0	0	1	0	0	0	0.73	2	15
3	1	0	0	0	1	0	0	0	1	0	0	0	0.73	3	11
4	1	0	0	0	0	0	1	0	0	0	0	0	0.70	2	10
5	0	0	0	0	0	1	0	0	0	0	0	0	0.68	1	63
6	0	0	0	0	0	0	0	0	0	0	0	1	0.67	1	27
7	1	0	0	0	0	1	0	0	0	0	0	0	0.66	2	41
8	1	0	0	0	0	0	0	1	0	0	0	0	0.66	2	29
9	1	1	0	0	0	0	0	0	0	0	0	0	0.63	2	63
10	0	0	1	0	0	0	0	0	0	0	0	0	0.63	1	64
11	0	1	0	0	0	0	0	0	0	0	0	0	0.63	1	56
12	0	0	0	0	0	0	0	1	0	0	0	0	0.62	1	121
13	0	0	0	0	0	0	1	0	0	0	0	0	0.61	1	36
14	1	0	0	1	0	0	0	0	0	0	0	0	0.60	2	10
15	1	1	0	0	0	1	0	0	0	0	0	0	0.55	3	11
16	1	0	0	0	0	0	0	0	0	0	0	0	0.54	1	200
17	1	0	0	0	1	0	0	0	0	0	0	0	0.51	2	71
18	0	0	0	1	0	0	0	0	0	0	0	0	0.47	1	45
19	0	0	0	0	0	0	0	0	1	0	0	0	0.43	1	69
20	0	0	0	0	1	0	0	0	0	0	0	0	0.38	1	121
21	0	0	0	0	0	0	0	0	0	1	0	0	0.36	1	14
22	0	0	0	0	0	0	0	0	0	0	1	0	0.30	1	270
23	0	0	0	0	0	0	0	0	0	0	0	0	0.14	0	32528

the commonality between these configurations. Only 10 of the 23 dominant case configurations indicated that the presence of more than one facility type results in a high harm street segment.

The results present in Table 6.4 can also allow for comparisons of common risk factors within three separate groups within the data: 1) those risk profiles with greater than the overall mean risk of a street segment having a high harm score (more than one standard deviation above); 2) those with substantially lower than mean risk (more than one standard deviation below); and, 3) those that fall within one standard deviation above and below the mean (Miethe et al., 2008). These are indicated by the horizontal lines between Configurations 3 and 4, 14 and 15, and 19 and 20 in Table 6.4.

The overall mean risk is 0.57 (SD =0.16). When examining the case configurations with the largest relative risk differences, the common feature among these four configurations is the absence of convenience stores (greater than one standard deviation above the average relative risk), fast food restaurants, gas stations, liquor and alcohol retail stores, lodging facilities, law enforcement agencies, schools, and smoke shops. All but one configuration indicated that the presence of at least one pharmacy created a higher than average risk of a street segment having a high harm score. AT least one ATM was present in each of these configurations.

Those with lower than average relative risk differences (more than one standard deviation below average) had the common feature of having almost no crime generator and attractor present, as was the case for those configurations with a relative risk difference within one standard deviation of the mean. Law enforcement agencies only contributed to the presence in of harm spots in one configuration with lower than average relative risk differences.

It should be mentioned that conjunctive analysis of case configuration models have the ability to empirically observe and handle complex multi-way interaction effects. These interaction effects, which are often unwieldy in traditional regression models, can include all variables included in the model. The current model, therefore, could allow researchers to investigate a 12-way interaction. Despite the fact that there was no evidence a full 12-way interaction, there was evidence that an interaction of facility types was affecting the risk of a harm spot being present. In the ten configurations with the largest relative risk difference, seven included the presence of more than one facility type. Most commonly among such configurations, street segments with ATMs and at least one other facility type occurred most often.

6.7 Discussion and Conclusions

Study #3 provides an exploratory examination of environmental risk factors related to high-harm harm spots by using two validated analytical techniques that can identify where contexts in which high-harm harm spots are more probable and the unique configurations of risk factors that surround high-harm harm spots. This research contributes to the existing literature by further exploring the predictors of serious crime and provides law enforcement with pertinent information to decrease the degree of harm that can result from serious crime.

There were three research questions being addressed in Study #3. Is there a discernable context for high-harm versus low-harm crimes? Are there unique configurations of potential crime generators and attractors at harm spots? Do these configurations differ at high-harm and low-harm harm spots? The simple overall answer is that no specific discernable context was identified for high-harm street segments. Lodging facilities, drinking establishments, and smoke shops had the top three largest main effects. This is consistent with previous research, such that alcohol draws a significant number of potential offenders and victims to a central location (i.e., crime attractors) and is often involved when crime is being committed (see for example, Groff & Lockwood, 2014). Hotels and other lodging facilities may also potentially draw in a significant number of victims, as they generally house individuals that may be less familiar with the area, but also act as crime attractors and generators of violent, drug, and sex crimes (LeBeau, 2012). Their vehicles may also be full of personal belongings that meet the requirements for target suitability and provide additional opportunities for offending.

However, in the CACC, the combination of ATMs and at least one additional facility type were present in the top five case configurations with the highest relative risk differences. ATMs and pharmacies were present in two of the top three case configurations with the highest relative risk difference. The results did not seem to indicate any specific combination of crime generators or crime attractors increased the likelihood of a street segment having a higher harm score, but the results do indicate that it is the total context interactively that must be evaluated for prediction and crime count/harm reduction.

The CACC was used to specifically address the second question regarding unique configurations of crime generators and crime attractors that are characteristic of high-harm harm spots. As this study is largely exploratory, the results that are presented here should only indicate that more research needs to be done to better understand the context in which high-harm harm spots occur. To review, CACC is capable of handling complex multi-way interactions that are often unwieldy in regression models. In that aspect, the contextual variability is easier to tease out using such models. No 12-way interactive effect was identified, which the model is capable of estimating. However, ATMs and at least one other facility type were present in nearly all configurations with the highest relative risk differences.

Despite all facility types being significant in the logistic regression models, ATMs and pharmacies were present in configurations with the largest relative risk differences in the CACC, indicating 1) that perhaps the combination of facilities is more important to consider, and 2) that those facilities with the largest main effects perhaps lose strength when one considers the total environment combined on

There are limitations of the Study #3 that should be addressed. The first is that the facilities here were derived from lists of crime generators and attractors that have been used in previous research attempting to explain the spatial patterns of hot spots (Caplan & Kennedy, 2011), or unweighted crime volume, but it is by no means a complete list of environmental risk factors that can be investigated to help explain why high-harm crimes occur where and when they do. Based on the findings of the CACC, the combination of ATMs and other facility types seemed to most frequently contribute to the largest relative risk differences, emphasizing the need to further research to understand the full context of the opportunity structure and the environmental elements that contribute to it. ATMs may contribute to higher rates of theft, robbery, and violence if people are being victimized as they leave a machine with money. But this also raises questions about what sort of contexts that ATMs can be found in that are also contributing to create settings that are more conducive to creating a high harm area. Hotels and bars are likely to be in some of the street segments as ATMs, which may be why the main effects of these facilities were so large in the regression models. Future research should focus on the combination of facilities, rather than the main effects of these facility types.

Second, harm can be a largely subjective measure. The CHI does attempt to overcome this with an objective measure using sentencing guidelines, but this index does not account for the emotional harm caused to the victim, nor does it account for any economic harm done to society during the commission of an offense. Cumulative measures of harm that include these components may be much better indicators of harm, but for the purposes of harm spot research, the existing literature does indicate that using the CHI is a viable proxy measure of harm. There are other potential indices or sources for weights that should be explored in future research to determine if a better scale exists to measure harm.

In conclusion, there is a significant amount of research that can be done in order to understand the distribution of harm using the methods employed in this study. Lodging facilities, drinking establishments, and smoke shops emerged as significant risk factors for street segments with high harm scores in both the regression models. However, there was also evidence that combinations of facility types and understand the context of the offense is a better approach to understanding where crime and harm are more likely to accumulate

7. DISCUSSION AND CONCLUSION

7.1 Introduction

The current dissertation explored the relatively new method of harm spot mapping, which is primarily based in the same theoretical concepts and methodological processes associated with the well-known hot spots mapping. Hot spots have been investigated at length for the last thirty years, originating with Sherman, Gartin, and Buerger's (1989) seminal article that described how most crime concentrated within only 3% of the addresses in Minneapolis over the course of the year. Separately, the literature on attempting to identify a measurable difference in offenses by weighting them by a harm score developed over the last fifty years. This literature originated with the work of Sellin and Wolfgang (1964), in which the authors sought to develop a ratio-level scale to weight crime by its relative harm. But only recently have the two disparate literatures together, resulting in the development of harm spot research, in which crime, weighted by its relative harm score, is spatially and temporally examined under the same theoretical concepts that guide hot spots research.

In general, the results indicate that different ecological processes underlie the spatial and temporal distribution of harm, and that crime generators and attractors previously utilized in the literature have some effect on the where high-harm crimes occur. While the present dissertation did not fully investigate the ecological processes that may be guiding the distribution of harm, the findings presented in this dissertation do at least provide a springboard for future research examining the distribution of harm. The concluding chapter of this dissertation will provide a brief summary of the preceding chapters (and Studies #1, #2, and #3) and a summary of the analyses and findings. This will be followed by a discussion of the implications for theory, policy and practice, and directions for future research. This chapter will end with a conclusion derived from all findings presented in this dissertation.

7.2 Summary of Chapters and Papers

The preceding chapters of this dissertation describe three studies that were conducted on harm spots to better understand how harm is distributed in time and space. Study #1 (Chapter 4) examined two research questions. The first question asked if the CHI could be used with the U.S. Sentencing Guidelines in order to develop an index for weighting crime by its relative harm score in the United States. The second question asked, once an index was developed, did the distribution of harm differ from the distribution of crime in space. The findings of Study #1 indicated that 1) the use of the CHI based on the U.S. Sentencing Guidelines was a good place to start for measuring crime harm, and 2) that the distribution of harm did differ from the distribution of unweighted crime.

Following this logic, Study #2 (Chapter 5) continued in the same vein by ultimately asking if the results found in Study #1 (Chapter 4) were generalizable. This study also examined temporal patterns in harm as well, as this replicated the research that has been completed examining harm in the United States (see for example Ariel, Weinborn, & Sherman, 2016; Curtis-Ham & Walton, 2017a; House & Neyroud, 2018; Norton et al., 2018; Weinborn et al., 2017). Both Study #1 (Chapter 4) and Study #2 (Chapter 5) examined the distribution of harm in the United States, as previous research has only been conducted internationally (e.g., in the United Kingdom, in New Zealand, and in Western Australia). Study #2 examined patterns in the distribution of crime harm spatially, temporally, and then spatiotemporally, as time and space are both important theoretical constructs derived from the theories providing the foundation for the three studies.

Harm was found to be focused in the same areas where crime volume generally clusters. It was largely centered on the interstate that bisects the city of Austin, Texas (I-35). However, as one moves away from the interstate, harm seems to decrease, despite some of these distant areas being crime volume hot spots. It is possible that access to a major travel artery is key to offenders' decisions to commit crimes with higher harm scores. It is important to remember that some harm spots are based on the accumulation of low-harm, high-volume offenses, and are not necessarily only a result of the commission of more rare, high-harm crimes.

Additional analyses examined the distribution of average harm scores over five different intervals of time: the full eleven years of data, annual variation by month, monthly variation by date, weekly variation by weekday, and daily variation by hour of day. The data were not complete, but supplemental analyses indicated that the results replicated previous research (for example, Weinborn et al., 2017). Generally, the distribution of the percentages of total harm and of total crime seemed to be highly correlated, following very similar patterns over each time period. When compared to average harm scores, harm scores seemed to follow a somewhat inverted distribution compared to what was found for the percent of total crime and total harm. This was specifically noticeable in the weekly distribution by weekday and the daily distribution by hour of day. The most harmful interval of time was in the very early hours between

4:00 AM and 7:00 AM, the most harmful day was Sunday, and winter had higher average harm scores than the rest of the months of the year.

The spatiotemporal analysis largely followed these findings, as well. The location of harm ultimately shifted from year to year. These distinct spots appeared to merge over time, and then remain consistent however, toward the later years of available data. In 2009, a harm spot emerged in a southwestern residential area and remained a harmspot throughout the data, regardless of which time interval was being examined.

Study #3 (Chapter 6) was developed as a follow-up of Study #1 (Chapter 4) and Study #2 (Chapter 5). The first two studies only examined the distribution of crime in space and time, while Study #3 attempted to provide context to these findings. Ultimately, the results indicated that lodging facilities, drinking establishments, smoke shops, and ATMs in combination with at least one other facility were important risk factors for harm. The results of all three studies indicated that 1) including harm in the spatial and temporal analysis of crime provides a more comprehensive assessment of what makes a hot spot "hot," and 2) that examining the full context of the environment is helpful in understanding where higher harm areas may be.

7.3 Implications for Theory

Routine activity theory (Cohen & Felson, 1979), crime pattern theory (Brantingham & Brantingham, 1993; 1995), and the effect of land use on the emergence, seasonality, diffusion, and stability of crime have a rich existing literature that has contributed to the understanding of the way crime behaves in space and time. Criminologists understand that opportunity and rational choice ultimately determine the decision to offend, and that individual routine behaviors and cognitive mapping largely determine where and when these offenses occur. However, Study #1 (Chapter 4) and Study #2 (Chapter 5) indicate that accounting for the relative harm of an offense results in a non-random pattern of criminal offending that may be slightly different to those non-random patterns associated with the simple accumulation of crime volume.

This has implications for theory as it indicates that some different, or additional, ecological process is guiding the occurrence of offenses with higher relative harm scores. There are implications under the opportunity and rational choice perspectives, specifically those that potentially inspire one to examine what risk factors are associated with the choice to commit crimes with higher relative harm at specific places and at specific times. Additionally, one may wonder what opportunity structures are preferable for these more harmful crimes to occur. Specifically, when examining the data from Washington, DC, it seemed that property crimes were being committed in areas where the likelihood of being caught for offending would be greatest. These crimes clustered largely in the downtown areas where crime generators and attractors were more numerous. Conversely, harm noticeably diffused from the city center into areas where clustering of suitable targets and crime generators and attractors was less probable.

Under the rational choice model, offender decision-making is largely influenced by the benefits that are associated with lower harm offenses and the suitability of targets as described by Clarke (1999). Clarke’s (1999) CRAVED model is based on the concept of target suitability originally described in Cohen and Felson’s (1979) description of routine activity theory. The CRAVED model stands for concealable, removable, available, valuable, enjoyable, and disposable, which simply describe the desirable properties of a suitable target. In the case of low-harm scoring offenses, such as theft or theft from a car, the cost of getting caught is not that high, and suitable targets are likely to be small and easily transported away from the offending location. For example, modern cell phones easily return a profit in exchange for very little work to obtain them through illegal means. They are also easily concealable in a pocket, of a size and weight that makes them easily removable, incredibly valuable, and there is a market for jail-broke iPhones and Android phones.

Advances in technology have important implications for theory as well. Wallets and cell phone cases with RFID blockers are being manufactured to decrease the risk of credit card fraud, as this information can be taken as one walks by a potential target. Such inventions and progressions are allowing for technologically advanced target hardening strategies, but also create additional opportunities for offending. This also changes the offending context significantly, as one can be victimized in a busy area, but not realize it for several hours, or even days.

Additionally, newer models of Samsung Galaxy phones use NFC technology to share information over wireless transfers. Apple product users have the ability to opt into AirDrop transfers, through which, *any* Apple user in a specific radius are able to receive “drops” from another user’s device. Both of these technologies are generally used to bolster and improve social media and communication, but all technological progress has more sinister implications and uses for those that are savvy enough to use them for criminal purposes. This changes the central tenets of many criminological theories, as it becomes less and less necessary to physically interact with potential human or inanimate targets to victimize them.

Routine activity and crime pattern theory are adaptable to technological advances. Routine behaviors occur in time and cyberspace, and cognitive mapping (a construct relevant to crime pattern theory) is applicable for internet use. While users may be less aware of the capabilities of technology, collection of usage data and public living through social media make it easier and easier to track routine behaviors in cyber space. These technologies are meant to be utilized for individualized marketing strategies. However, as Brantingham and Brantingham indicate, the awareness spaces of offenders and victims are likely to be indistinguishable, and are likely overlapping quite frequently. For example, offenders and non-offenders likely have a presence on social media on one of the main platforms. Facebook, Twitter, Reddit, Tumblr, and Instagram are all popular social media platforms of which most people are aware.

Other implications can be derived from the spatial findings in Study #2 (Chapter 5), in which the importance of major transportation routes became more apparent. Crime pattern theory focuses on several concepts, including awareness and activity spaces, nodes, paths and edges. While more potential crime generators and attractors may be along major roadways, this in and of itself may not be the only important factor involved in an offender's decision to commit an offense.

Finally, there is a clear indication in the literature that survey respondents find a qualitative difference between different crime types, which allows them to rank crimes by their relative harm consistently across contexts. There is also a distinct ranking of violent versus property crimes, in which respondents consistently rank violent crimes as having greater relative harm than property crimes. As such, there may be *prima facie* justification to consider these different crime types separately when addressing the spatial distribution of harm in a jurisdiction. However, as research indicates that most offenders do not specialize, it is possible that it would follow that most *locations* are analogously unspecialized. Instead it is the opportunity structure created by the location that changes the amount of harm that may occur there. For example, an offender can offender can commit a robbery in the same location as they may perform a sexual assault, so long as the location provides the opportunity to do so. This has further implications for opportunity theories, in that it supports the notion that the context of the offense is an important consideration in understanding offending behaviors.

7.4 Implications for Policy and Prevention

The obvious contribution for policy and practice with this research is that there are implications for improving officer safety, resource allocation, and crime prediction considerations. Research in hot spots analysis and mapping has allowed researchers to develop software that police departments can use to better deploy officers to areas where the most crimes occur. It is generally accepted that, with continued employment, seasoned officers likely know what to expect in the areas that they are patrolling, but new and rookie officers are less likely to have this knowledge when they get on patrol. It is also known that police departments place an emphasis on officer safety.

The findings from this research not only provides police departments and crime analysts with empirical evidence supporting the use of the CHI scale to weight their maps, but it also indicates that those areas that tend to be low in crime, may sometimes emerge as a harm spot. These areas are those with higher risk of victimization, though the crimes are arguably less severe, specifically with the harm caused to the victims. Larceny-theft cases were the most common crimes to occur every year that was included in the preceding studies, implying that the largest cost to the victim was having to replace something that was taken. Policies that implement and increase situational awareness and crime prevention may be more helpful in these areas, rather than direct patrol.

With additional research, future studies can determine if family and domestic violence provides an explanation for the distribution observed in Study #1. The maps in this study show that harm diffuses away from the city center and follows its own non-random patter that appears to be concentrated in residential areas. Study #2 and Study #3 did not include any family and domestic violence cases to understand harm as it applies in overt crimes. However, these offenses are also more likely to take place in residential areas. While there may be additional understanding to come from testing the difference between overt and covert crimes, understanding where more serious offending with more serious consequences is likely to occur may help guide policy about how to patrol more effectively to make places objectively safer, rather than just decreasing crime counts.

7.5 Implications and Directions for Research

In line with the implications for policy and practice, future research should investigate whether past harm has any sort of predictive power for future harm. For example, broken windows theory posits that physical and social disorder are just indicators to potential offenders that the members of that particular community care little for their neighborhood and, therefore, are less likely to intervene on or prevent further disorder from occurring. If an area is objectively dangerous, it may be helpful to understand what effects this has on the area over time, as well as the areas nearby to determine how harm affects both crime and harm distribution and diffusion.

Future research should also investigate the effect that the built environment has on harm. Study #3 (Chapter 6) and the dissertation in general only examined one aspect of the built environment and the effect that has on the emergence of harm spots in an urban jurisdiction. No consideration was made for vegetation, lighting, CCTV, or any other number of environmental design aspects. Crime Prevention Through Environmental Design (CPTED) was first described by Newman (1972) and is largely influenced by the work of Jeffrey (1971). CPTED examines how design elements effect the crime rate.

It is likely that people often conflate fear of harm/fear of crime with fear of victimization. The fear of crime literature often indicates that there is a difference between fears of crime and victimization, and that this is ultimately a gendered phenomenon. Women are often socialized to believe that they are weaker and less able to defend themselves. The anxiety of considering what may happen when they are alone is likely driving a fear of victimization, despite no rational or logical expectation to fear that a crime will actually occur. Therefore, men are less likely to report being fearful than women. However, despite this, it is possible that fear of victimization could be based in factual relativism. Recent research has used mapping techniques to identify the spatial distribution of fear of crime. This may provide an insight to the types of crimes that are occurring in a location.

Additional research questions should be addressed regarding the interaction between the type of crime that is committed and the ambient population in the area. Cohen and Felson (1979) state that the mere presence of a capable guardian is sufficient to prevent a crime from occurring. The majority of offenses are committed in areas that are often densely populated with pedestrian traffic. Most often, these crimes have low relative harm scores, and pose very little threat or cost to the potential victim or target. Under routine activity theory, the targets in these crimes often fall under the CRAVED model, and likely include money, phones, purses, etc. However, despite the presence of dozens, or even hundreds, of capable guardians, these areas are often the most crime prone, even if they are not truly dangerous.

Finally, future research should consider *all* the available crime offenses in calls-for-service data. Recall that the total number of offenses in Austin, Texas recorded between 2007 and 2017 was nearly 550,000 offenses. However, when only examining "traditional" crime types (those recorded and reported in UCR reports annually by the FBI), and when excluding family and dating violence cases, this resulted in a sample size of under 200,000. Following Weinborn et al. (2018), developing a full "menu" of crimes in a specific jurisdiction is highly recommended, as this allows for both nuanced crime indices, as well as prevents future researchers from excluding potentially important information in their data.

7.6 Concluding Comments

The research presented in the dissertation above sought to expand the existing literature on mapping harm in space and time, and trying to understand if, how, and why harm is distributed in a different non-random distribution than unweighted crime volume. While this is largely exploratory research, there are a few conclusions that can be drawn from the findings presented above. First, and foremost, harm adds a necessary component to the spatial and temporal clustering patterns observed in crime data. Though the differences were not always notable, those that were observed in the temporal patterns in Study #2 showed that harm has the potential to distribute in time and space following different non-random patterns than crime volume. Felson and Clarke (1998) indicate that there are distinct opportunity structures for each distinct criminal offense, which perhaps indicates that the external influences and offender decision-making process in the commission of an offense are unique as well. This is likely what is causing the empirically observed differences in the distribution of harm in time and space.

Second, crime harm seems to occur when and where no one is looking, or when the offender is less likely to be caught. There are a couple possibilities that may explain this as harm is likely operating under a unique form of routine activity theory that places an emphasis on the role of guardianship. As guardianship is a largely understudied concept in routine activity theory, research focusing on the effects of guardianship on harm is recommended.

Third, harm requires further investigation in general. The relationship between volume and harm is tricky, as volume creates superficial harm spots in densely trafficked areas due to the sheer volume of offenses that accumulate in these areas. But this violates and supports assumptions from routine activity theory: more suitable targets increase the likelihood of victimization, but an increase in the number of potential guardians should decrease this very same probability. These areas only highlight places where a sort of nuisance victimization is likely to occur, rather than real physical victimization.

Additionally, while lodging facilities, drinking establishments, and smoke shops were consistently identified as risk factors for high harm scores on a street segment, there was little convincing evidence that if some sort of policy were put into practice by hotel or bar staff that this would reduce the likelihood of crime. In Washington, DC, and in Austin, Texas, it seemed that harm was often clustered both in more residential blocks and along major roadways, which means that commercial facilities may not fully explain why higher harm crime occurs where and when it does.

APPENDIX SECTION

APPENDIX A – HARM INDICES FOR STUDY #1

Appendix 1. Offense definitions used to calculate median harm scores from the U.S. Sentencing Guidelines, based on Sherman et al.'s (2016) Crime Harm Index (CHI).

Offense Type	Median [a]
Sex Abuse [b]	32.0
Aggravated sexual abuse under 18 U.S.C. §2241(c)	38.0
Sexual abuse by force, fraud, or coercion of children under 14 years old, under 18 U.S.C. §1591(b)(1)	34.0
Other aggravated sexual abuse	30.0
Other aggravated sexual abuse of minors	14.0
Homicide	25.5
First degree murder (Statutory Provisions: 18 U.S.C. §§ 1111, 1841(a)(2)(C), 1992(a)(7), 2113(e), 2118(c)(2), 2199, 2282A, 2291, 2332b(a)(1), 2340A; 21 U.S.C. § 848(e))	43.0
Second degree murder (Statutory Provisions: 18 U.S.C. §§ 1111, 1841(a)(2)(C), 2199, 2282A, 2291, 2332b(a)(1), 2340A)	38.0
Voluntary manslaughter (Statutory Provisions: 18 U.S.C. §§ 1112, 1841(a)(2)(C), 2199, 2291, 2332b(a)(1))	29.0
Involuntary manslaughter involving the reckless operation of a means of transportation	22.0
Involuntary manslaughter involving reckless conduct	18.0
Involuntary manslaughter involving criminal negligence	12.0
Robbery	20.0
Such offenses include "thefts from the person by means of force or fear" (p. 109) Departures may occur with aggravating circumstances (e.g., discharging a firearm or brandishing a deadly weapon); however, the base line offense is listed with a score of 20	20.0

Offense Type	Median
Arson *	18.0
“…if the offense (A) created a substantial risk of death or serious bodily injury to any person other than a participant in the offense, and that risk was created knowingly; or (B) involved the destruction or attempted destruction of a dwelling, an airport, an aircraft, a mass transportation facility, a mass transportation vehicle, a maritime facility, a vessel, or a vessel’s cargo, a public transportation system, a state or government facility, an infrastructure facility, or a place of public use…” (p. 257)	24.0
“…if the offense (A) created a substantial risk of death or serious bodily injury to any person other than a participant in the offense; (B) involved the destruction or attempted destruction of a structure other than (i) a dwelling, or (ii) an airport, an aircraft, a mass transportation facility, a mass transportation vehicle, a maritime facility, a vessel, or a vessel’s cargo, a public transportation system, a state or government facility, an infrastructure facility, or a place of public use; or (C) endangered (i) a dwelling, (ii) a structure other than a dwelling, or (iii) an airport, an aircraft, a mass transportation facility, a mass transportation vehicle, a maritime facility, a vessel, or a vessel’s cargo, a public transportation system, a state or government facility, an infrastructure facility, or a place of public use…” (p. 257)	20.0
“…if the offense involved the destruction of or tampering with aids to maritime navigation…” (p. 257)	16.0
“…2 plus the offense level from §2B1.1 (Theft, Property Destruction, and Fraud)…” (p. 257)	2.0
Motor Vehicle Theft	18.0
Carjacking	22.0
Organized scheme to steal vehicles/parts	14.0
Burglary	14.5
Of a residence	17.0
Of a structure other than a residence	12.0

Offense Type		Median
Aggravated Assault		15.0
	"…a felonious assault that involved (A) a dangerous weapon with intent to cause bodily injury (i.e., not merely to frighten) with that weapon…" (p. 60) Departures may occur with aggravating circumstances (e.g., discharging a firearm or brandishing a deadly weapon); however, the base line offense is listed with a score of 14.	14.0
	"…if the offense (A) created a substantial risk of death or serious bodily injury to any person other than a participant in the offense; (B) involved the destruction or attempted destruction of a structure other than (i) a dwelling, or (ii) an airport, an aircraft, a mass transportation facility, a mass transportation vehicle, a maritime facility, a vessel, or a vessel's cargo, a public transportation system, a state or government facility, an infrastructure facility, or a place of public use; or (C) endangered (i) a dwelling, (ii) a structure other than a dwelling, or (iii) an airport, an aircraft, a mass transportation facility, a mass transportation vehicle, a maritime facility, a vessel, or a vessel's cargo, a public transportation system, a state or government facility, an infrastructure facility, or a place of public use…" (p. 257)	20.0
	"…if the offense involved the destruction of or tampering with aids to maritime navigation…" (p. 257)	16.0
	"…2 plus the offense level from §2B1.1 (Theft, Property Destruction, and Fraud)…" (p. 257)	2.0

Offense Type	Median
Theft [c]	6.5
Includes the following offenses: "larceny, embezzlement, and other forms of theft; offenses involving stolen property; property damage or destruction; fraud and deceit; forgery; offenses involving altered or counterfeit instruments other than counterfeit bearer obligations of the United States" (p. 88) "…if (A) the defendant was convicted of an offense referenced to this guideline; and (B) that offense of conviction has a statutory maximum term of imprisonment of 20 years or more…" (p. 88)	7.0
Other theft not described above	6.0
Other Assault	4.5
"…if the offense involved physical contact, or if a dangerous weapon (including a firearm) was possessed and its use was threatened…" (p. 61)	7.0
An assault otherwise not described above	2.0

[a] Scores were rounded to the next highest value; the lowest sentence length (in months) in the range associated with that number in the Sentencing Guidelines Table was selected to calculate to the harm score (calculated in sentence length in days, as suggested by Sherman et al., 2016).

[b] Calculations for sex abuse exclude trafficking and commercialized sex offenses.

[c] This is a collapsed category that includes both general theft and theft from an automobile; the descriptions of larceny/theft in the U.S. Sentencing Guidelines did not distinguish between the two.

***** Indicates an offense in which the base line offense score calculation includes instructions to apply the greatest score

Appendix 2. Offense scenarios from the National Survey of Crime Severity (NSCS; Wolfgang et al., 1985) used to calculate the median harm scores for the NSCS scale.

Offense Type	Median
Homicide	39.1
A person plants a bomb in a public building. The bomb explodes and 20 people are killed.	72.1
A man forcibly rapes a woman. As a result of physical injuries, she dies.	52.8
A parent beats his young child with his fists. As a result, the child dies.	47.8
A person plants a bomb in a public building. The bomb explodes and one person is killed.	43.9
A person robs a victim at gunpoint. The victim struggles and is shot to death.	43.2
A man stabs his wife. As a result, she dies.	39.2
A factory knowingly gets rid of its waste in a way that pollutes the water supply of a city. As a result, 20 people die.	39.1
A person stabs a victim to death.	35.7
A person intentionally injures a victim. As a result, the victim dies.	35.6
A woman stabs her husband. As a result, he dies.	27.9
A factory knowingly gets rid of its waste in a way that pollutes the water supply of a city. As a result one person dies.	19.9
A person kills a victim by recklessly driving an automobile.	19.5
Knowing that a shipment of cooking oil is bad, a store owner decides to sell it anyway. Only one bottle is sold and the purchaser dies.	17.8
Arson	22.3
A person intentionally sets fire to a building causing $100,000 worth of damage.	24.9
A person intentionally sets fire to a building causing $500,000 worth of damage.	22.3
A person intentionally sets fire to a building causing $10,000 worth of damage.	12.7

Offense Type	Median
Sex Abuse	20.1
A man forcibly rapes a woman. Her physical injuries require hospitalization.	30.0
A man forcibly rapes a woman. No other physical injury occurs.	25.8
A man tries to entice a minor into his car for immoral purposes.	25.2
A man forcibly rapes a woman. Her physical injuries require treatment by a doctor but not hospitalization.	20.1
A man runs his hands over the body of a female victim, then runs away.	5.1
A man exposes himself in public.	4.7
A person makes an obscene phone call.	1.9
Aggravated Assault	16.4
A person plants a bomb in a public building. The bomb explodes and one person is injured bur no medical treatment is required.	33.0
A person plants a bomb in a public building. The bomb explodes and 20 people are injured but no medical treatment is required.	30.5
A person intentionally shoots a victim with a gun. The victim requires hospitalization.	24.8
A parent beats his young child with his fists. The child requires hospitalization.	22.9
A person intentionally shoots a victim with a gun. The victim requires treatment by a doctor but not hospitalization.	19.0
A high school boy beats a middle-aged woman with his fists. She requires hospitalization.	19.5
A man beats his wife with his fists. She requires hospitalization.	18.3
A person stabs a victim with a knife. The victim requires hospitalization.	18.0
A person intentionally shoots a victim with a gun. The victim is wounded slightly and does not require medical treatment.	17.8
A high school boy beats an elderly woman with his fists. She requires hospitalization.	17.5
A person stabs a victim with a knife. The victim requires treatment by a doctor but not hospitalization.	17.1

Offense Type	Median
Aggravated Assault	16.4
A person attempts to kill a victim with a gun. The gun misfires and the victim escapes unharmed.	16.4
A teenage boy beats his mother with his fists. The mother requires hospitalization.	15.9
A person intentionally injures a victim. The victim is treated by a doctor and hospitalized.	11.9
A man beats a stranger with his fists. He requires hospitalization.	11.8
A person stabs a victim with a knife. No medical treatment is required.	11.8
Ten high school boys beat a male classmate with their fists. He requires hospitalization.	11.7
Three high school boys beat a male classmate with their fists. He requires hospitalization.	11.3
A person intentionally hits a victim with a lead pipe. The victim requires hospitalization.	10.4
A person intentionally .hits a victim with a lead pipe. The Victim requires treatment by a doctor but no hospitalization.	8.9
A teenage boy beats his father with his fists. The father requires hospitalization.	7.9
A person intentionally hits a victim with a lead pipe. No medical treatment is required.	7.9
A person beats a victim with his fists. The victim requires hospitalization.	6.9
Robbery	9.0
A person robs a victim of $1,000 at gunpoint. The victim is wounded and requires hospitalization.	21.0
A person robs a victim of $10 at gunpoint. The victim is wounded and requires hospitalization.	17.9
A person, armed with a gun, robs a bank of $100,000 during business hours. No one is physically hurt.	17.7
A person, using force, robs a victim of $1,000. The victim is hurt and requires hospitalization.	16.8
A person, using force, robs a victim of $1,000. The victim is hurt and requires treatment by a doctor but not hospitalization.	16.6

Offense Type	Median
Robbery (cont.)	9.2
A person robs a victim of $1,000 at gunpoint. The victim is wounded and requires treatment by a doctor but not hospitalization.	16.5
A person robs a victim of $10 at gunpoint. The victim is wounded and requires treatment by a doctor but not hospitalization.	15.7
A person, armed with a lead pipe robs a victim of $1,000. The victim is injured and requires hospitalization.	15.6
A person, using force, robs a victim of $10. The victim is hurt and requires hospitalization.	14.6
A person, armed with a lead pipe, robs a victim of $1,000. The victim is injured and requires treatment by a doctor but not hospitalization.	13.7
A person, armed with a lead pipe, robs a victim of $10. The victim is injured and requires hospitalization.	13.3
A person robs a victim of $1,000 at gunpoint. No physical harm occurs.	9.7
A person breaks into a display case in a store and steals $1,000 worth of merchandise.	9.7
A person robs a victim of $10 at gunpoint. No physical harm occurs.	9.4
A person, armed with a lead pipe, robs a victim of $1,000. No physical harm occurs.	9.0
A person, using force, robs a victim of $1,000. No physical harm occurs.	8.0
A person, armed with a lead pipe, robs a victim of $10. No physical harm occurs.	7.5
A person threatens a victim with a weapon unless the victim gives him money. The victim gives him $10 and is not harmed.	7.3
A person, armed with a lead pipe, robs a victim of $10. The victim is injured and requires treatment by a doctor but not hospitalization.	7.1
A person, using force, robs a victim of $10. The victim is hurt and requires treatment by a doctor but not hospitalization.	6.7

Offense Type	Median
Robbery (cont.)	9.2
A person does not have a weapon. He threatens to harm a victim unless the victim gives him money. The victim gives him $10 and is not harmed.	6.6
A person threatens to harm a victim unless the victim gives him money. The victim gives him $10 and is not harmed.	5.4
A person, using force, robs a victim of $10. No physical harm occurs.	5.1
A person snatches a handbag containing $10 from a victim on the street.	4.9
A person picks a victim's pocket of $100.	4.4
A person robs a victim. The victim is injured but not hospitalized.	4.4
A person picks a victim's pocket of $10.	3.3
A person forces open a cash register in a department store and steals $10.	3.1
Motor Vehicle Theft	8.0
A person steals a locked car and sells it.	10.8
A person steals an unlocked car and sells it.	8.0
A person steals an unlocked car and later abandons it undamaged.	4.4
Other Assault	7.3
A man drags a woman into an alley, tears her clothes, but flees before she is physically harmed or sexually attacked.	16.9
A person threatens to seriously injure a victim.	9.3
A person intentionally injures a victim. The victim is treated by a doctor but is not hospitalized.	8.5
A person beats a victim with his fists. The victim is hurt but does not require medical treatment.	7.3
Because of a victim's race, a person injures a victim to prevent him from enrolling in a public school. No medical treatment is required.	6.8

Offense Type	Median
Other Assault (con.t)	7.3
A person beats a victim with his fists. The victim requires treatment by a doctor but not hospitalization.	6.2
A person intentionally shoves or pushes a victim. No medical treatment is required.	1.5
Theft from Auto	6.6
A person steals $1,000 worth of merchandise from an unlocked car.	6.6
Burglary	5.9
A person breaks into a bank at night and steals $100,000.	15.5
A person breaks into a department store, forces open a safe, and steals $1,000.	9.7
A person breaks into a school and steals equipment worth $1,000.	9.7
A person breaks into a home and steals $1,000.	9.6
A person breaks into a department store and steals merchandise worth $1,000.	7.3
A person breaks into a public recreation center, forces open a cash box and steals $1,000.	6.9
A person breaks into a public recreation center, forces open a cash box, and steals $10.	4.3
A person breaks into a department store, forces open a cash register, and steals $10.	3.3
A person breaks into a building and steals property worth $10.	3.2
A person breaks into a school and steals $10 worth of supplies.	3.1
A person breaks into a home and steals $100.	3.1
A person breaks into a department store and steals merchandise worth $10.	2.8
Other Theft	3.3
A person steals property worth $10,000 from outside a building.	10.9

Offense Type	Median
Other Theft (con.t)	3.3
A person walks into a public museum and steals a painting worth $1,000.	9.7
A person trespasses in a railroad and steals tools worth $1,000.	7.9
A person steals $1,000 worth of merchandise from the counter of a department store.	7.6
A person steals property worth $1,000 from outside a building.	6.9
A person steals property worth $100 from outside a building.	3.6
A person steals property worth $50 from outside a building.	2.9
A person trespasses in a city-owned storage lot and steals equipment worth $10.	2.2
A person steals $10 worth of merchandise from the counter of a department store.	2.2
A person steals property worth $10 from outside a building.	1.7
A person breaks into a parking meter and steals $10 worth of nickels.	1.6
A person trespasses in a railroad yard and steals a lantern worth $10.	1.4

APPENDIX B – HARM INDICES FOR STUDY #2 AND STUDY #3

Appendix 3. Offense definitions used to calculate median harm scores from the U.S. Sentencing Guidelines, based on Sherman et al.'s (2016) Crime Harm Index (CHI) for Study #2 and Study #3.

Offense Type	Median	Weight [a]	Standardized
Aggravated Assault	17	720	6.67
Aggravated assault with strangulation/suffocation	17	720	6.67
Aggravated assault	14	450	4.17
Aggravated assault on a public servant	17	720	6.67
Aggravated assault with motor vehicle	17	720	6.67
Arson with bodily injury	20	990	9.17
Deadly conduct	19	900	8.33
Take weapon from a police officer	17	720	6.67
Arson	20	1230	11.39
Arson	20	990	9.17
Criminal mischief with arson	24	1530	14.17
Homicide	43	10800	100.00
Capital murder	43	10800	100.00
Manslaughter	29	2610	24.17
Murder	43	10800	100.00
Motor vehicle theft	18	810	7.50
Auto theft	18	810	7.50
Burglary	14.5	495	4.58
Burglary of a non-residence shed	12	300	2.78
Burglary of a non-residence	12	300	2.78
Burglary of a residence – sexual nature	17	720	6.67
Burglary of a residence	17	720	6.67

Offense Type	Median	Weight	Standardized
Robbery	23	1380	12.78
Aggravated robbery by assault	24	1530	14.17
Aggravated robbery with deadly weapon	27	2100	19.44
Robbery by assault	22	1230	11.39
Robbery by threat	22	1230	11.39
Rape/Forcible Rape	30	2910	26.94
Aggravated forced sodomy	38	7050	65.28
Aggravated forced sodomy of a child	34	4530	41.94
Aggravated rape of a child	34	4530	41.94
Aggravated assault of a child with an object	14	450	4.17
Aggravated rape	38	7050	65.28
Aggravated sexual assault with object	30	2910	26.94
Forced sodomy	30	2910	26.94
Rape	30	2910	26.94
Rape of a child	30	2910	26.94
Sexual assault of a child with an object	34	4530	41.94
Sexual assault with an object	34	4530	41.94
Larceny-Theft	6	30	0.28
Breach of computer security	6	30	0.28
Burglary of a coin-op machine	6	30	0.28
Misapplication fiduciary property	6	30	0.28
Pocket picking	6	30	0.28
Purse snatching	6	30	0.28
Theft	6	30	0.28
Theft by shoplifting	6	30	0.28
Theft of catalytic converter	6	30	0.28
Theft from a building	6	30	0.28
Theft from a person	6	30	0.28
Theft of auto parts	6	30	0.28
Theft of bicycle	6	30	0.28
Theft of heavy equipment	6	30	0.28

Offense Type	Median	Weight [a]	Standardized
Larceny-Theft	6	30	0.28
Theft of license plate	6	30	0.28
Theft of metal	6	30	0.28
Theft of trailer	6	30	0.28
Theft/till tipping	6	30	0.28
Burglary of an auto	12	300	2.78
Theft from auto	6	30	0.28

NOTES:

The offenses listed below each Part I Index Crime category were all the recorded offense sub-types recorded in all eleven years' of reported crime data from Austin Police Department.

[a] The lowest sentence length (in months) in the range associated with that number in the Sentencing Guidelines Table was selected to calculate to the harm score (calculated in sentence length in days, as suggested by Sherman et al., 2016).

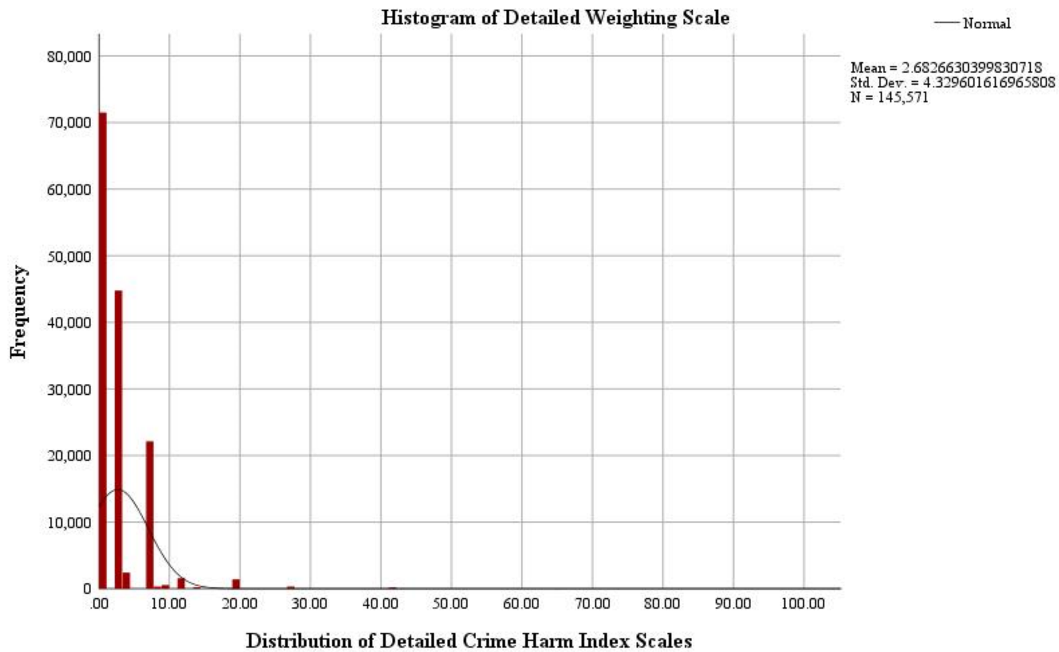
[b] Calculations for sex abuse exclude trafficking and commercialized sex offenses.

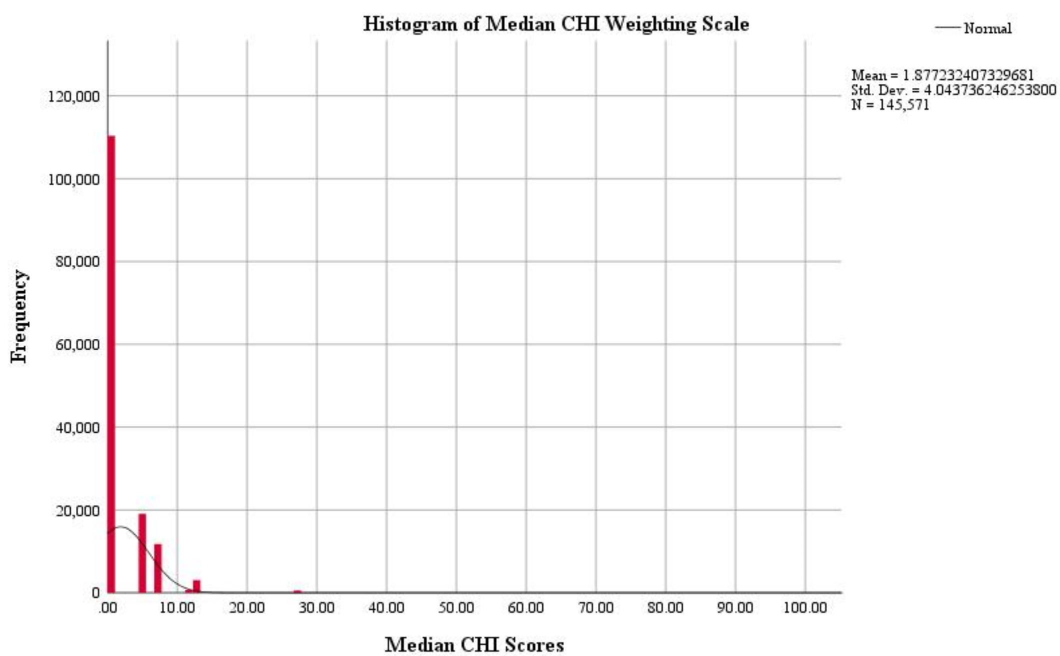
[c] This is a collapsed category that includes both general theft and theft from an automobile; the descriptions of larceny/theft in the U.S. Federal Sentencing Guidelines did not distinguish between the two.

* Indicates an offense in which the base line offense score calculation includes instructions to apply the greatest score

APPENDIX C – SUPPLEMENTAL ANALYSES

Analysis of Harm Scores





Two histograms were created to show how positively skewed the distribution of harm scores are for these data. The first histogram displayed above includes scores assigned to every offense sub-type included in these data (see Appendix B). This distribution is positively skewed (skew = 8.92) and leptokurtic (kurtosis = 164.01) and is far from normally distributed. The median harm score is 2.78 and the mean is 2.68 (SD = 4.33). The scale ranges from 0 to 100.

The second histogram displays the distribution of the median scores assigned to the Part I Index Crime categories. This is much more positively skewed (skew = 10.28) and leptokurtic (kurtosis = 219.07). The median harm score is 0.28, as nearly 80% of offenses have a relative harm score of 0.28. The average harm score is 1.88 (SD = 4.04). If the scores remain unstandardized, the average harm score is 202.59, which means that each individual offense receives a 6.75 month sentence on average. The scale is still based on the standardize range of 0 to 100.

There are two considerations that need to be made based on these graphs. First, with approximately 115,000 offenses having a harm score of 0.28, these offenses are likely to create a harm spot based on crimes that are high-volume-low-harm. Second, if a harm spot is comprised of low-volume-high-harm offenses, then there is a sort of violence effect for a street segment that may not necessarily be a location for high risk of victimization. This further supports the need for examining both crime volume and crime harm to fully understand the risk of victimization, and the risk for the type of victimization that will occur at a specific street segment.

Analysis of Total Crime Counts

As graphs were generated for the temporal analysis regarding the numbers of crimes that were committed over the eleven years included in this study, it became apparent that there were some data collection or reporting errors that resulted in incorrect crime reporting numbers for the years highlighted in red and yellow. The years highlighted in green represent data that is more likely to be expected in a city.

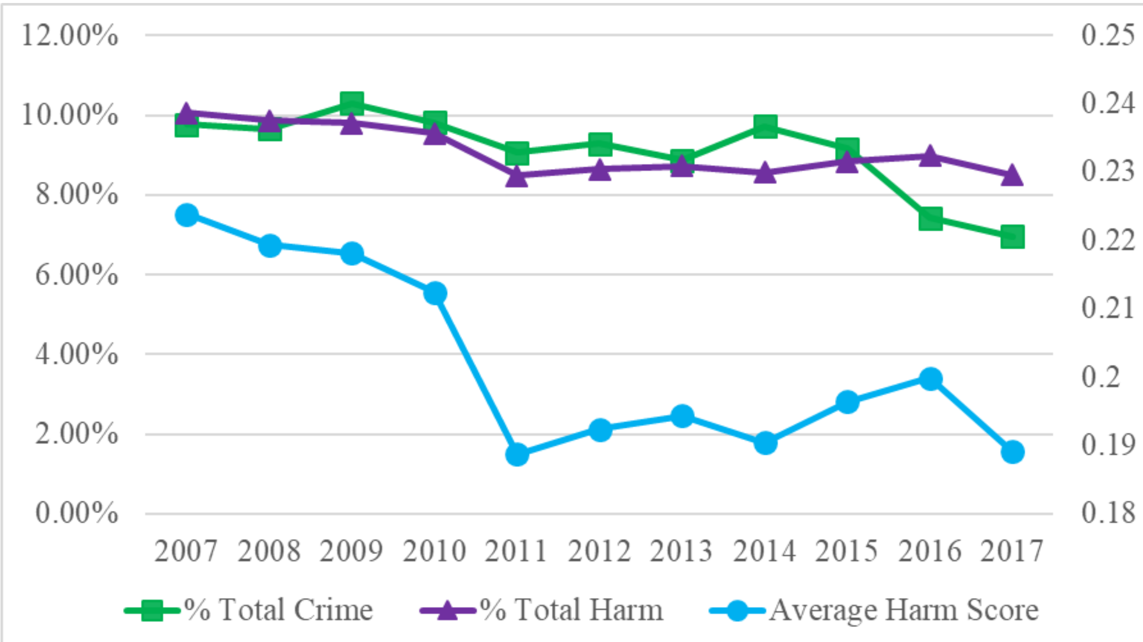
Year	Aggravated Assault	Arson	Auto Theft	Burglary	Homicide	Larceny-Theft	Rape	Robbery	Total
2007	15	32	28	34	0	150	107	14	380
2008	6	32	11	16	0	132	51	12	260
2009	4	23	9	18	0	134	14	3	205
2010	10	35	18	59	2	293	23	4	444
2011	893	98	1,231	3,958	17	21,102	59	690	28,048
2012	888	104	1,372	4,308	14	22,961	57	604	30,308
2013	977	78	1,326	3,755	12	22,443	26	480	29,097
2014	927	73	1,327	3,456	20	20,056	49	535	26,443
2015	980	77	1,289	2,987	18	19,100	83	594	25,128
2016	144	73	149	327	5	2,802	55	108	3,663
2017	95	82	57	130	1	1,170	23	37	1,595

However, when data from the Uniform Crime Reports (available on the FBI UCR website) were examined, the following table was generated:

Year	Aggravated Assault	Arson	Auto Theft	Burglary	Homicide	Larceny-Theft	Rape	Robbery	Total
2007	2,056	32	2,961	8,031	30	34,461	328	1,457	49,356
2008	2,306	32	2,633	8,586	23	33,582	273	1,333	48,768
2009	2,322	23	2,219	8,753	22	37,054	265	1,415	52,073
2010	2,256	35	2,250	8,749	38	34,827	265	1,231	49,651
2011	2,126	98	2,139	7,042	28	33,069	211	1,106	45,819
2012	2,187	104	2,315	7,244	31	33,913	209	978	46,981
2013	2,117	78	2,169	6,550	26	32,948	217	763	44,868
2014	2,105	73	2,288	5,733	32	37,444	*571	873	49,119
2015	2,058	77	2,331	5,000	23	35,399	*487	929	46,304
2016	2,065	**74	2,188	5,232	29	26,125	*751	1,048	37,512
2017	2,186	82	2,079	4,380	25	24,542	*834	987	35,115

* These data are reported using the newer UCR definition of rape.
** Only arson score identified in UCR data.

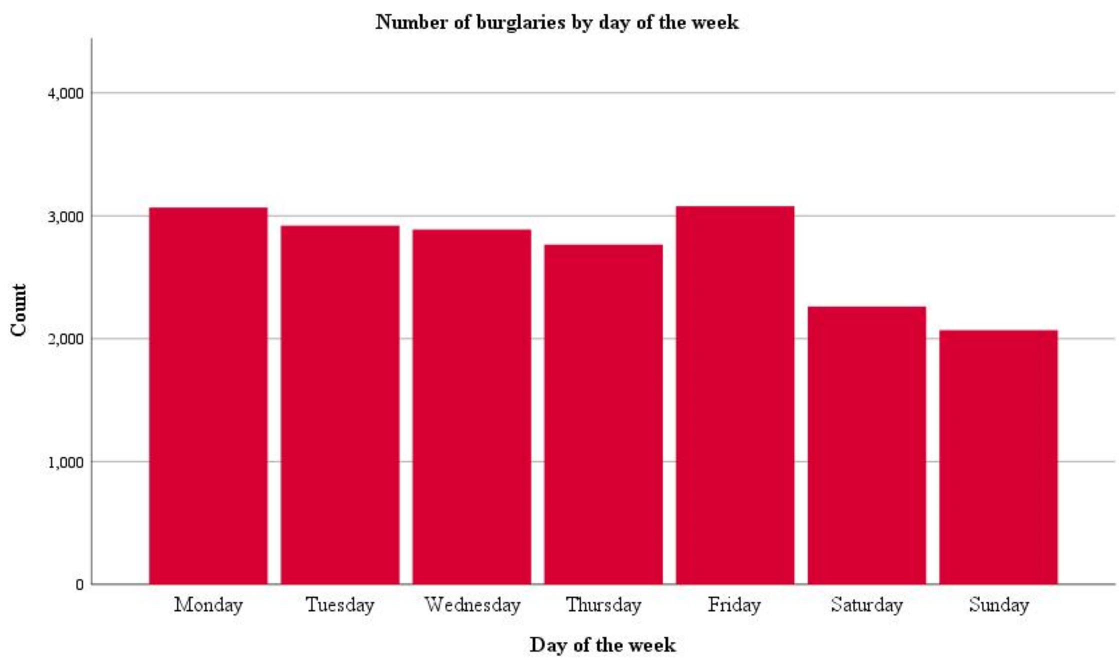
There are noticeably different values between the two tables, including the total number of crimes for each year included in the present study. This is simply a risk that is taken when utilizing data from an open data portal. However, these data were not useful for the remaining spatial and temporal analyses, as only those included in the study were geocoded with the date and time that they occurred to permit such analyses.



The UCR data displayed these trends. The average harm scores are driven by the number of larceny-theft cases every year. The general increase in the average harm score follows the change in the UCR definition of rape, the use of which began in 2013. The UCR table above shows that rape cases doubled following the change in definition, and may be one of the driving factors in the slight increase in the average harm score from 2011 to 2016. Despite the percent of harm and percent of total crime being nearly evenly distributed between all years, the average harm score notably decreased from 2007 to 2011.

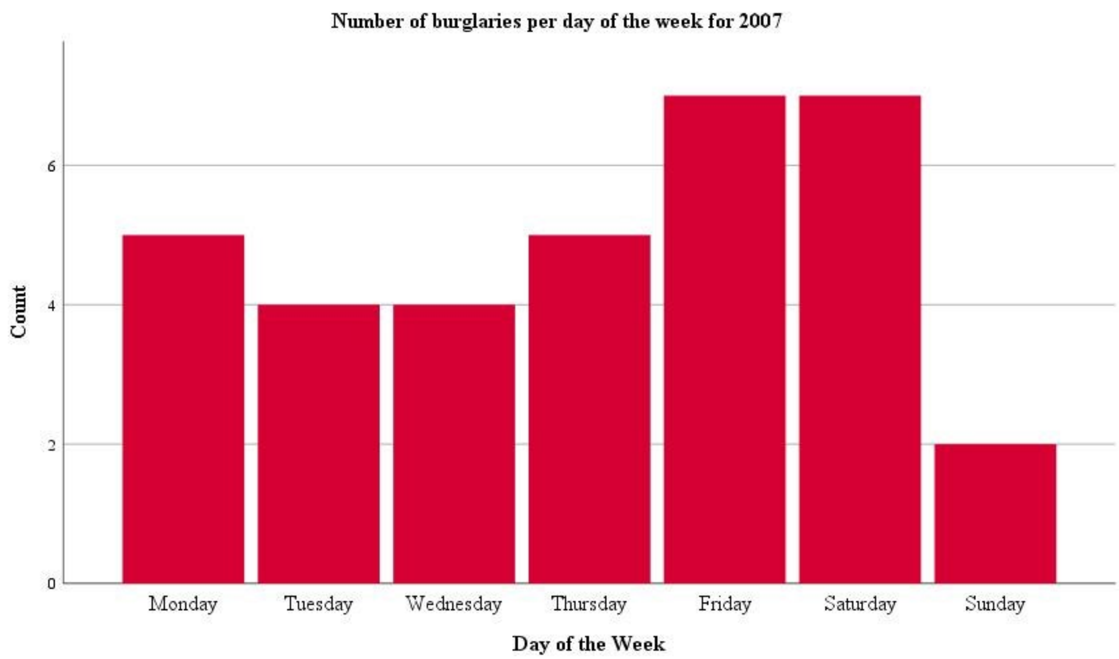
Analysis of Burglaries by Weekday

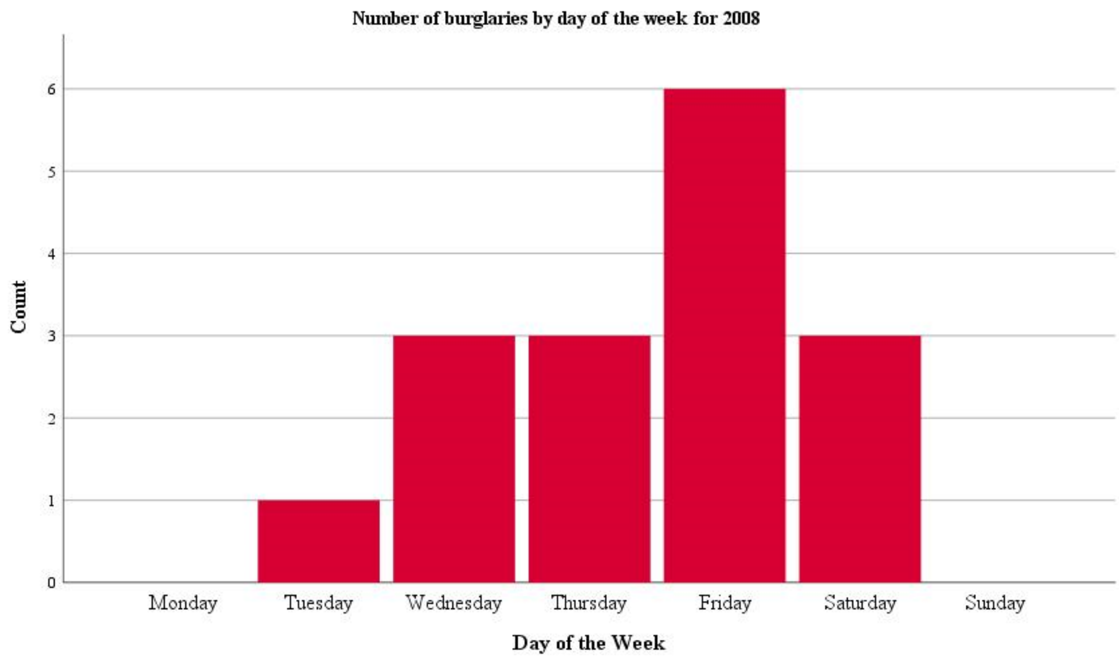
Burglaries were used to determine if there was any systematic bias in the distribution of crime types between the years of 2007 and 2010, and then for 2016 and 2017. It is generally known that burglaries occur more frequently during the weekdays, following the central tenets of routine activity theory (houses are without capable guardians during the daytime hours). When examining burglaries for all years, the data display this sort of trend. However, when examining the year of data with low numbers, this pattern disappears. For this reason, only the data for the years of 2011 to 2015 were used for the spatiotemporal analysis.

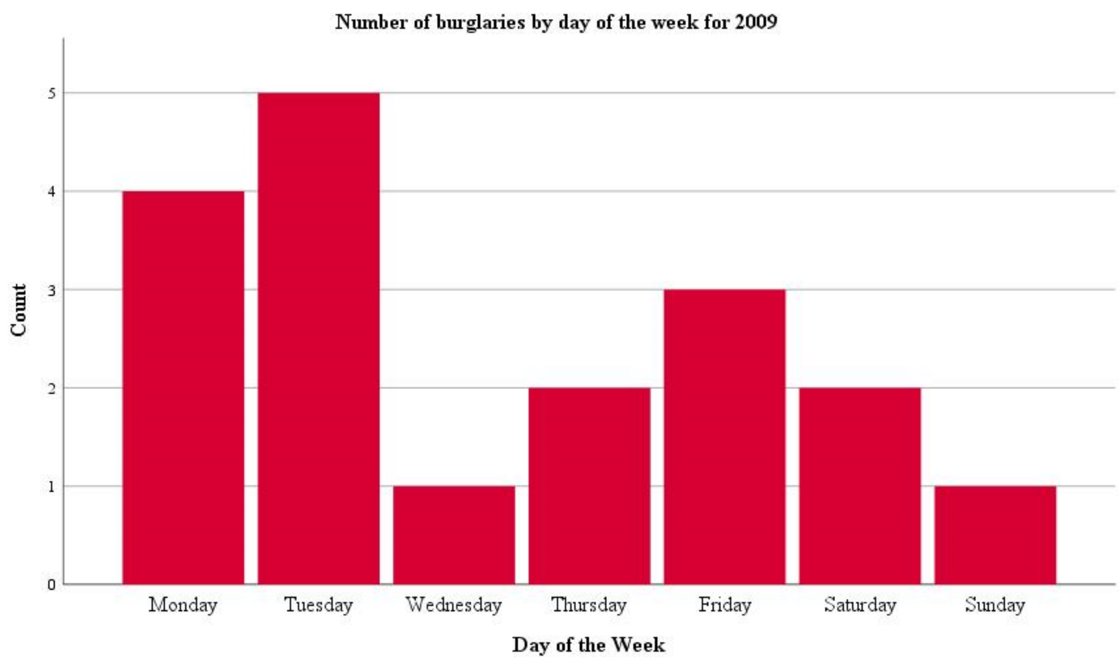


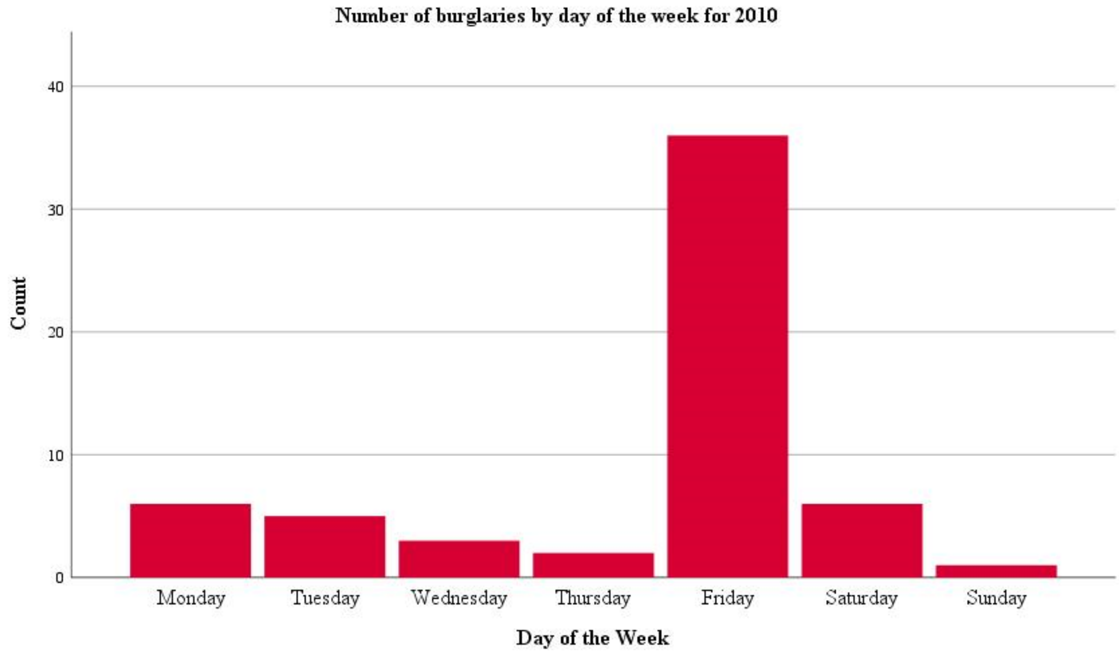
When examining the number of burglaries by weekday in the graphs below, very few of them follow the expected weekly pattern of burglaries. However, the data from 2011 to 2015 follow the expected weekly pattern of burglaries. The years of 2016 and

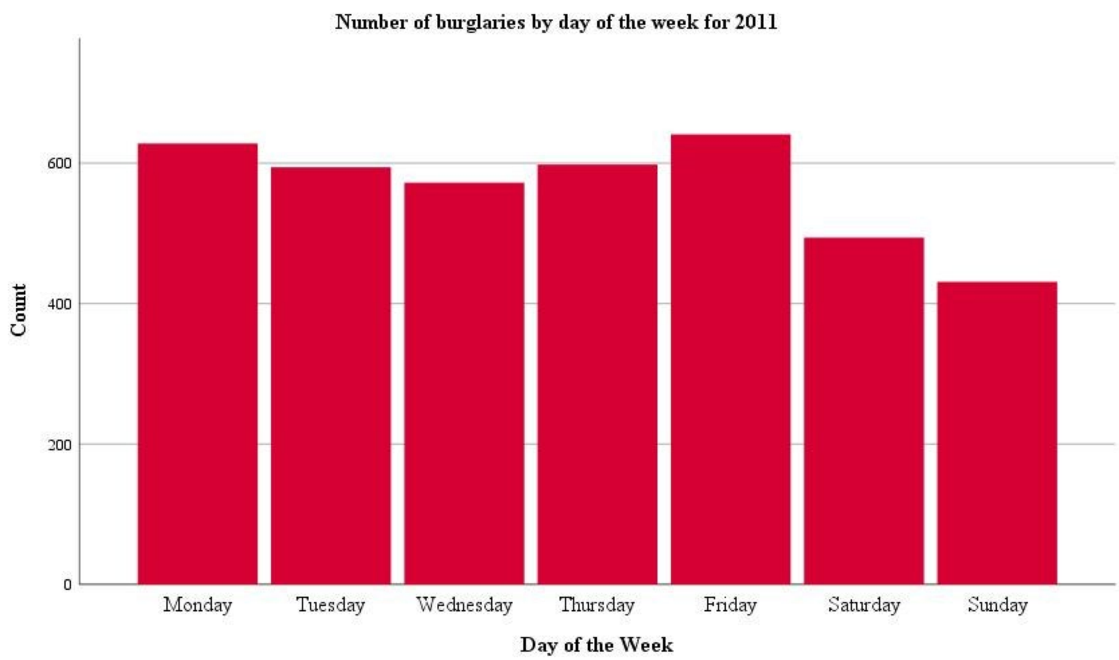
2017 had many more crimes recorded than the years of 2007 to 2010, and they generally followed the weekly pattern of burglaries, but to ensure that the results were more stable, these years were excluded from the analysis as well. The Federal Bureau of Investigation UCR website recorded approximately 37,000 (37,448) offenses for 2016, and 35,033 offenses for 2017.

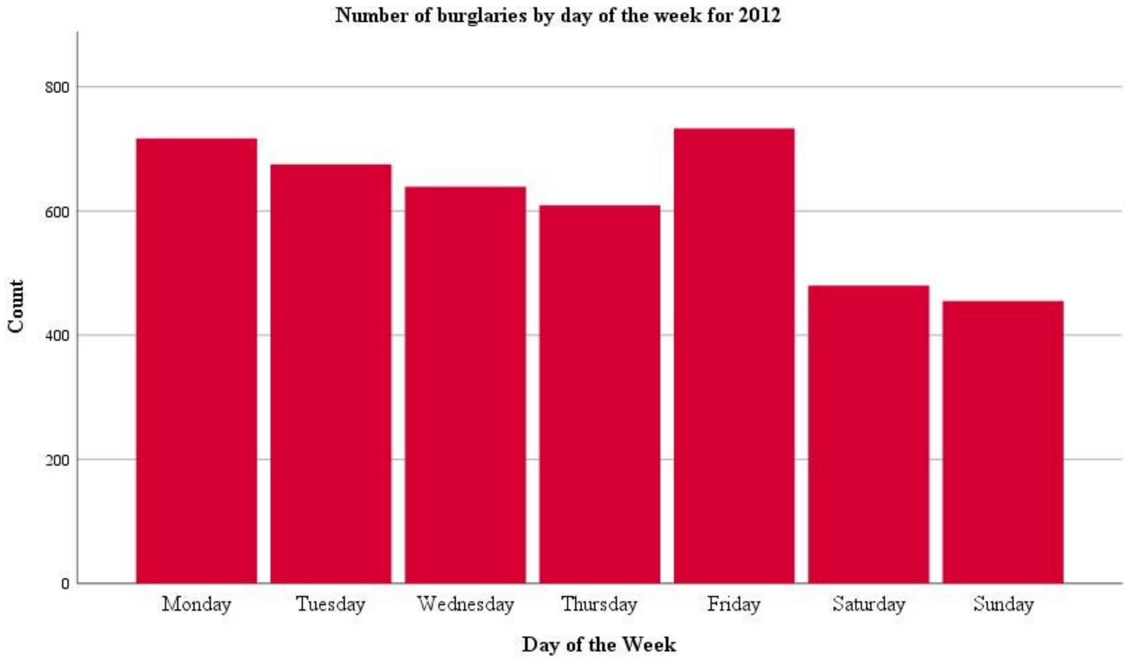



Number of burglaries by day of the week for 2008
Count
6
5
4
3
2
1
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of the Week

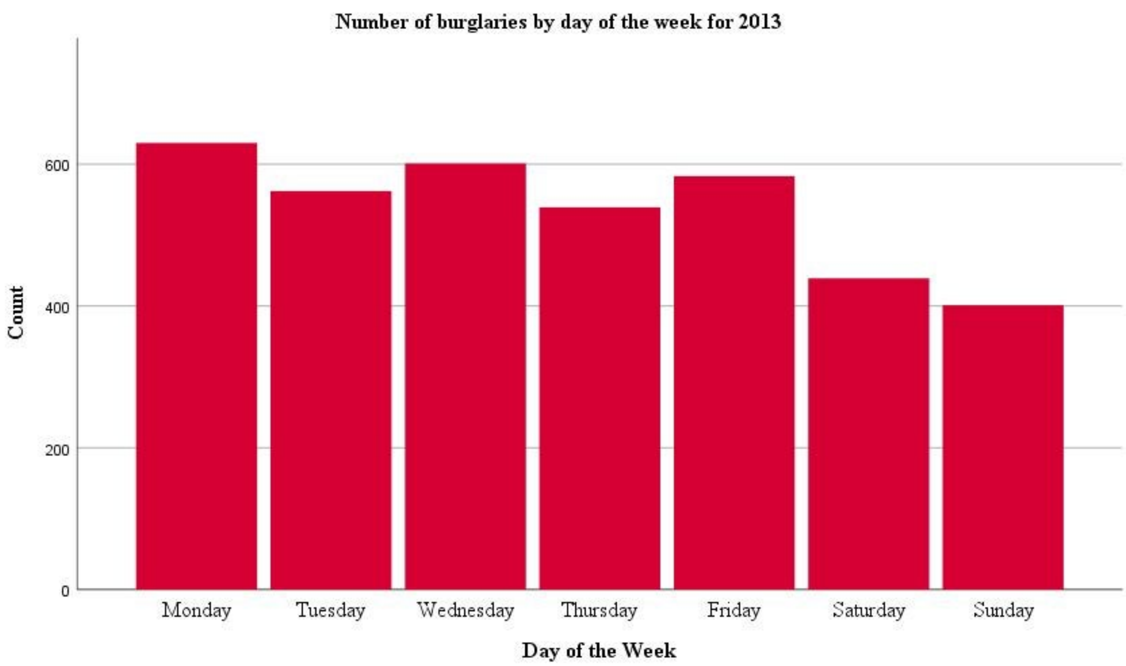

Number of burglaries by day of the week for 2009
Count
5
4
3
2
1
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of the Week


Number of burglaries by day of the week for 2010
Count
40
30
20
10
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of the Week

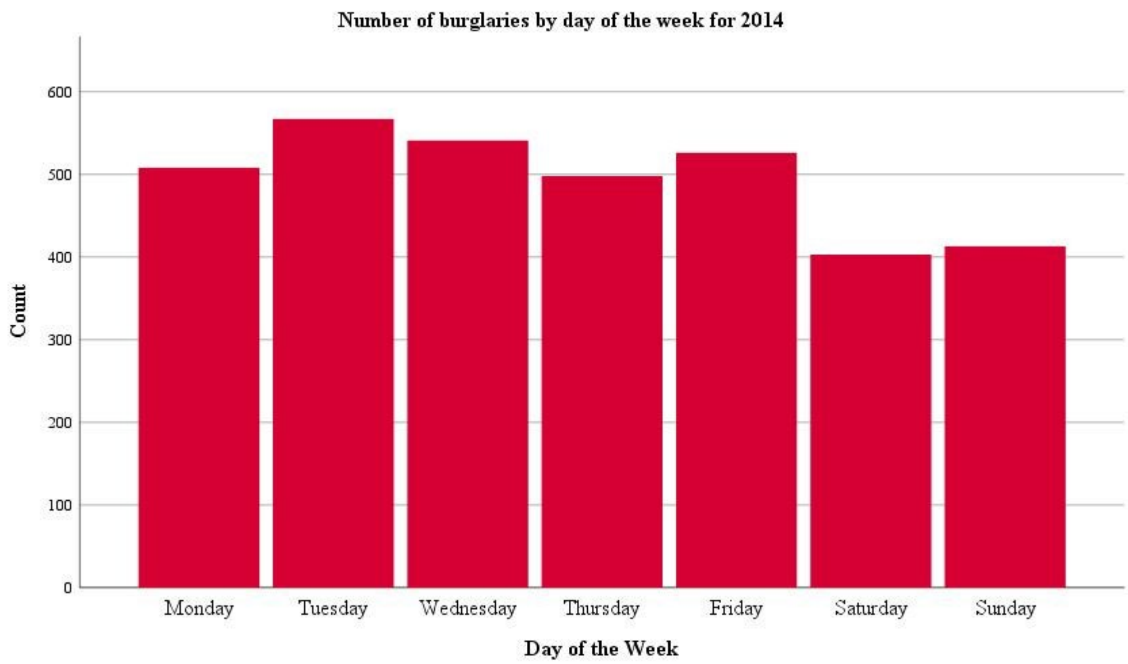

Number of burglaries by day of the week for 2011
Count
600
400
200
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of the Week

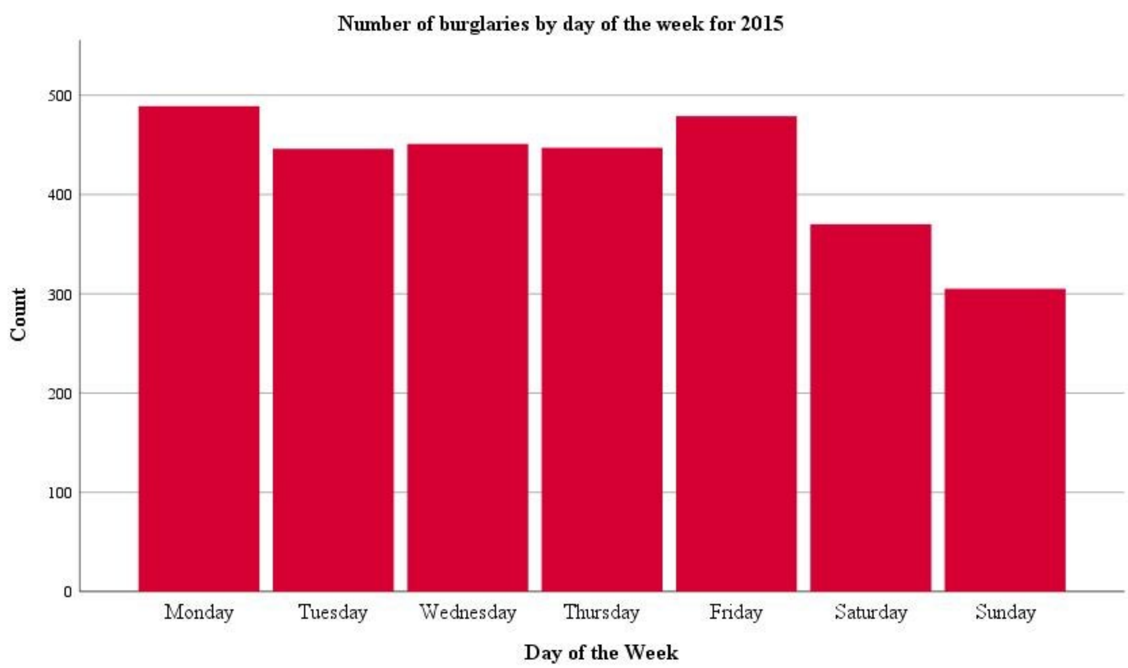


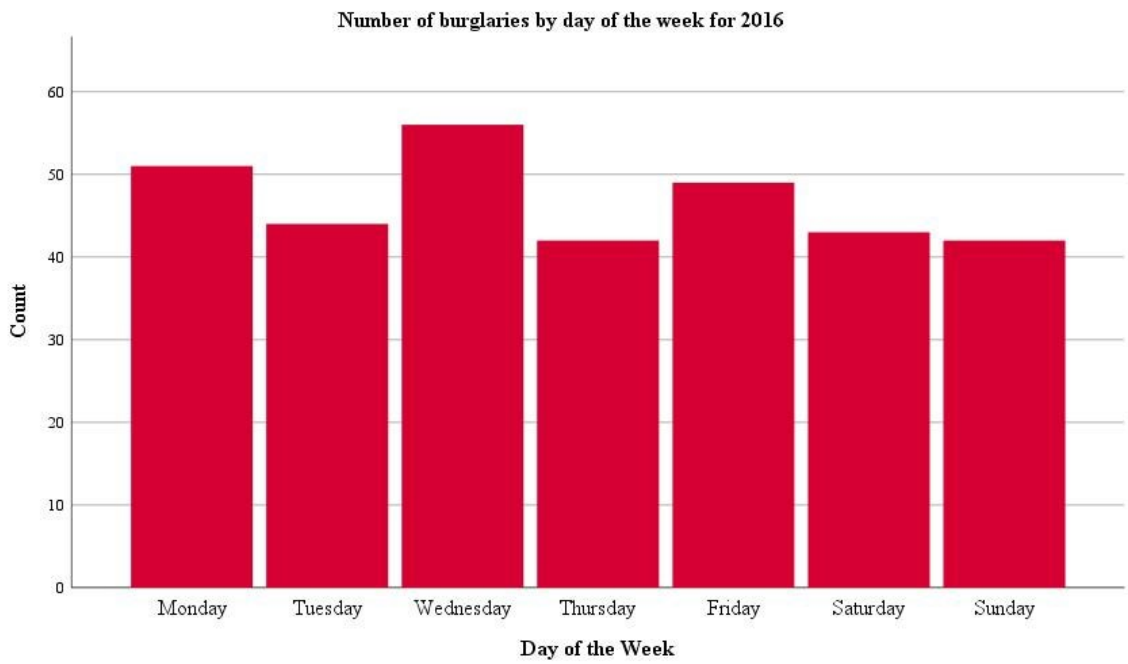
Number of burglaries by day of the week for 2012
Count
800
600
400
200
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of the Week

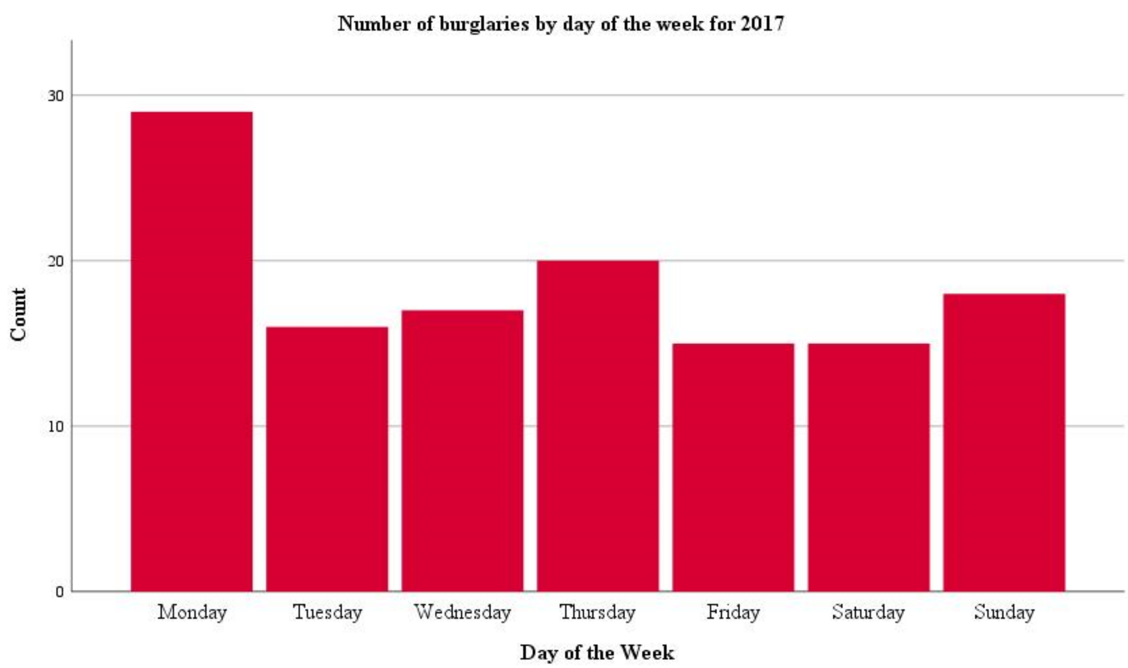


Number of burglaries by day of the week for 2013
Count
600
400
200
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of the Week


Number of burglaries by day of the week for 2014
Count
600
500
400
300
200
100
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of the Week

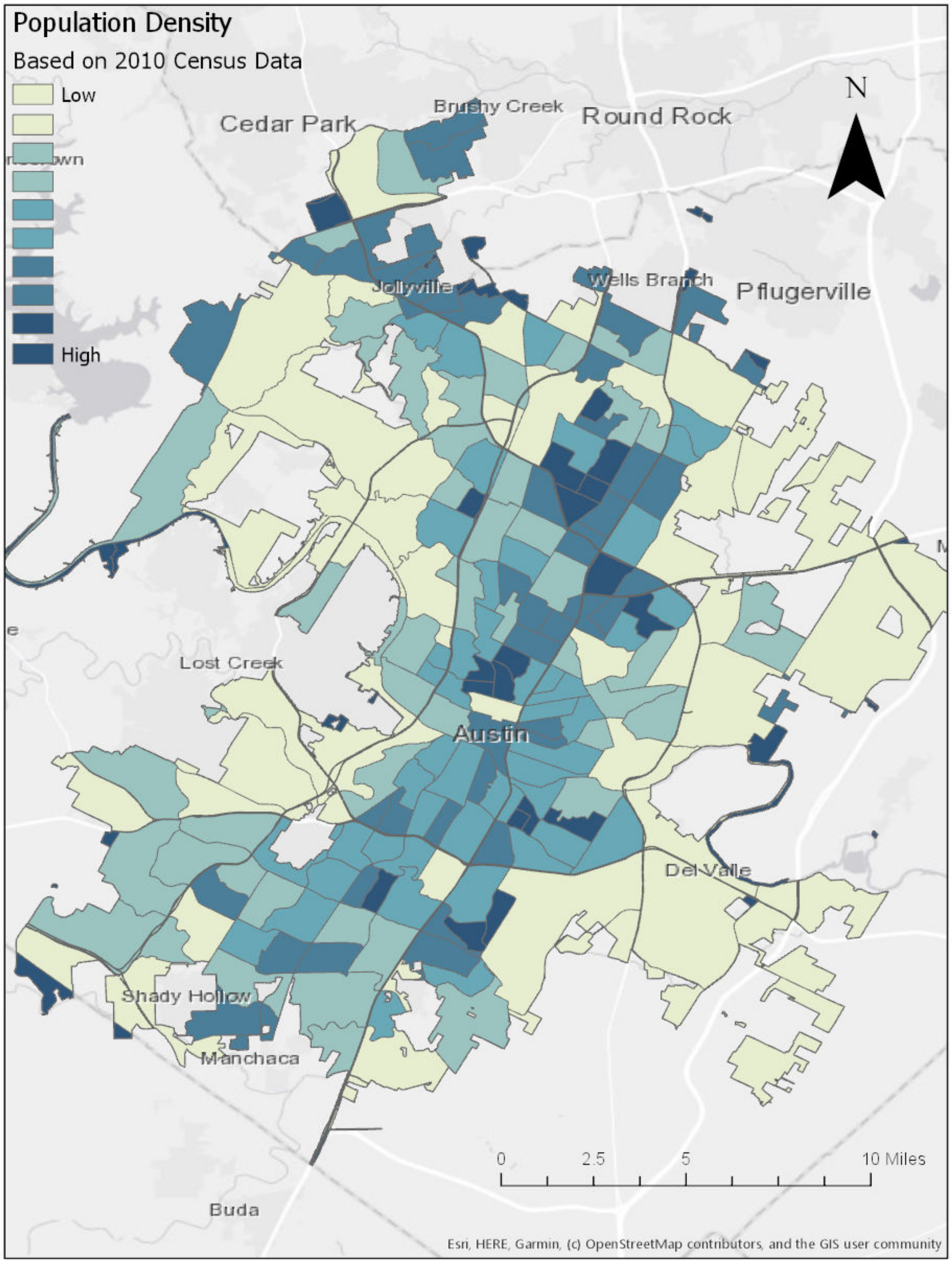

Number of burglaries by day of the week for 2015
Count
500
400
300
200
100
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of the Week


Number of burglaries by day of the week for 2016
Count
60
50
40
30
20
10
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of the Week

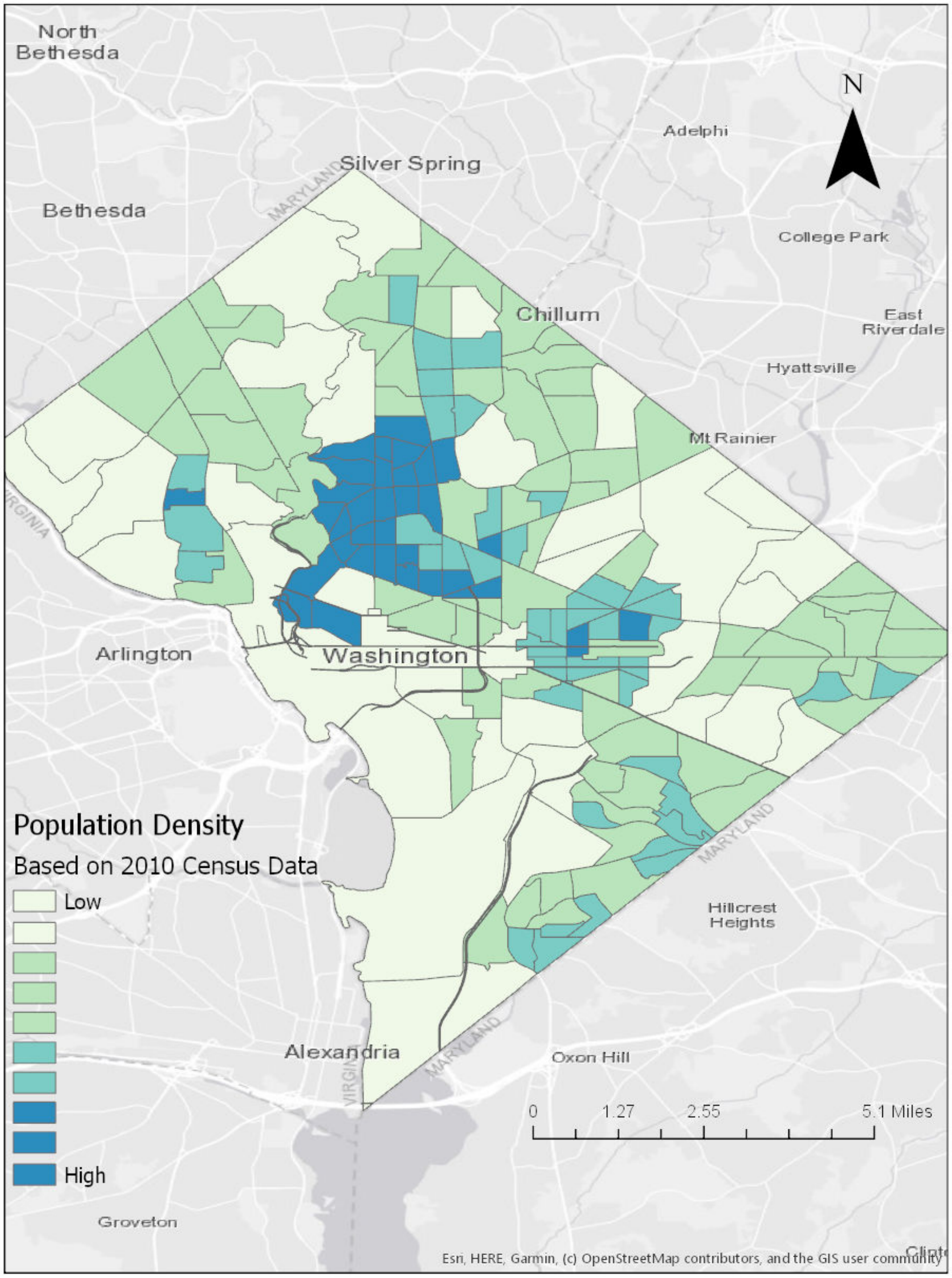

Number of burglaries by day of the week for 2017
Count
30
20
10
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of the Week

Population Density Maps for Austin, TX and Washington, DC

Population Density Map for Austin, TX, based on 2010 Census Data



Population Density Map for Washington, DC, based on 2010 Census Data



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