The Spatial Variability of Crime: A Review of Methodological Choice, Proposed Models, and Methods for Illustrating the Phenomenon

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THE SPATIAL VARIABILITY OF CRIME: A REVIEW OF METHODOLOGICAL CHOICE, PROPOSED MODELS, AND METHODS FOR ILLUSTRATING THE PHENOMENON

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DEDICATION

I dedicate this work to my beautiful daughters, Paisley Grace and Presley Emerson.

You have taught me more than any book or classroom ever could.
ACKNOWLEDGEMENTS

Nothing is accomplished alone. I have many people to thank for helping me reach this moment. First, I want to thank Cory Schnell for taking on the huge responsibility of being my co-chair and mentoring me from my first moments on campus. You are as cool as McConaughey. To my dissertation committee, Bob Kaminski, Ashley Mancik, and Andrew Lemieux, thank you for keeping an open mind and allowing me the freedom to explore my true interests. To everyone in the Department of Criminology and Criminal Justice, thank you for the invaluable support while studying at the University of South Carolina. I also want to thank Rachel Boba Santos, Egan Green, and Riane Bolin for their support as it has been beyond what I ever expected to need. If it were not for them, I likely would not have ended up here.

Finally, my sincerest gratitude goes to my beloved wife, Allie. In the short time we spent in South Carolina, we have shared the darkest and brightest moments imaginable. Through those times, we have only grown closer, and I am greatly appreciative of everything you have provided me.
ABSTRACT

The spatial analysis of crime has occurred for nearly two centuries. Within criminology, research interests that have developed from the use of spatial methodologies seek to identify the spatial variability and concentration of crime. The first focus utilizes spatial statistics and mapping to describe and illustrate spatial variability. The second focus uses statistical techniques to describe levels of concentration such as the percentage of crime attributed to a unit. Due to the larger breadth of work and multiple analytical components the former will be the focus of this research.

This multi-study dissertation explores the methods currently used to study the spatial variability of crime, presents a novel method to do so within and between U.S. cities, and demonstrates innovative ways to illustrate it. The first study is a systematic review of the literature on the spatial variability of crime during the last decade (2010-2019). Using protocols based on a systematic literature review this study reviews the relevant literature and reports on the methods and findings of selected research. Trends were identified that show a lack of cohesiveness across the studies regarding choice of methodology and unit selection. However, an emphasis on using micro-units was observed across the studies. The second study explores the spatial variability of crime within and between U.S. cities. Variance partitioning of multi-level models were estimated to observe the crime variance attributed to each unit of analysis. The majority of the spatial variability of crime can be attributed to micro-units. However, larger spatial
units provide greater context within cities and particularly between cities as spatial
variability was observed to vary among the examined cities. The third study highlights
the importance of crime mapping and explores methods to map the spatial variability of
crime. Innovative techniques such as dynamic maps are used to illustrate the adaptability
of crime mapping and suggestions are made for their continued use. Overall, this
dissertation contributes to the crime and place literature by examining past
methodologies, presenting new ones, and incorporating mapping into research on the
spatial variability of crime.
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CHAPTER 1

INTRODUCTION

Interest in exploring the relationship of the spatial variation of crime is not a novel concept. From the 19th century to present, research findings have consistently found that crime is unevenly distributed across cities (Guerry, 1833; Sampson, 2012; Shaw et al., 1929; Weisburd et al., 2012). Crime and place research is an encompassing term that describes the sub-field of criminological research focusing on the variation of crime across geographic areas. This sub-field is a departure from traditional criminological research that primarily focuses on explaining criminal behavior. Since the Chicago School, scholars have observed how crime varies across urban landscapes and how it concentrates at a few places relative to a much larger geographic backdrop (see Eck & Weisburd, 1995; Shaw & McKay, 1942; Sherman et al., 1989; Weisburd, 2015). Over the last two decades and combined with new computational abilities to do so, analyzing crime through a geographic lens has gotten much more advanced. Technological advancements are continually creating new opportunities for spatially analyzing crime. Broadly, there are two research foci within modern crime and place research. These are the statistical concentration of crime and the spatial variability of crime (also referred to as distribution).

While much empirical support exists for both research interests, as of late, scholarly interest has been directed towards empirically testing the law of crime
concentration (see Weisburd, 2015). Research involving micro-places is also abundant as crime is often most concentrated to these areas. Often overlooked though are studies analyzing crime across multiple spatial levels and those that focus on how crime varies within cities or between-city comparisons. The methods applied to study crime concentration are typically limited to statistical descriptions such as the Lorenz curve and Gini coefficient. Research analyzing the spatial variability of crime has a much wider range of methodological choices that are dependent on multiple factors such as unit choice and spatial weighting. Because no clear framework exists regarding studying the spatial variability of crime this dissertation sets out to use the topic as the basis for its three studies.

The remainder of this introductory chapter provides an explanation for why crime and place research matters and the differences between crime concentration and the spatial variability of crime. The motivations for this dissertation will also be discussed. The final section briefly outlines the three studies comprising this work.

**Place Matters**

Historical interest in crime and place research is evident, however, it is not until the last few decades that considerable attention on the topic has occurred. Much of the latest interest has grown from advancements in technology and theory. Research during the Chicago School observed crime at the neighborhood level due to convenience and was largely limited to descriptive exploration (Shaw & McKay, 1942). The complexities of conducting spatial analyses pre-computers limited much of what could be explored during the Chicago School. Of more recent times, the hot spot, is a type of spatial concept
possible for study only due to the existence of computer technology. Calculating large-scale hot spot analyses by-hand is not feasible. The recent trend to analyze crime at the street segment, a micro-place, is also only possible using computer technology. The technological advancements over the last 40 years have greatly contributed to the flourishing body of crime and place work.

Theoretical advancements have also increased interest in crime and place research and two perspectives guide much of it. The dominant perspective is the opportunity-based theoretical spectrum which includes the routine activities, crime pattern, and rational choice theories (Brantingham et al., 2017; Cornish & Clarke, 2017; Felson & Eckert, 2019; Quick et al., 2018; Weisburd et al., 2012, 2016). As a precursor to their crime pattern theory, the Brantinghams (1981) aptly stated that of the four dimensions of every crime, a spatial dimension is one. The other theoretical perspective used in crime and place research is based on the social disorganization theory (Sampson, 2012). This theory has roots from the Chicago School with recent updates to include sociological characteristics that go beyond “place” such as the concept of collective efficacy. While immensely popular, the social disorganization theory is less often used compared to the opportunity theories. There have been growing calls to integrate theories such as routine activities and social disorganization to provide better understandings of how crime occurs across space (see Jones & Pridemore, 2019). While each of the theoretical perspectives play an important role in framing research, they do little to inform the methodologies necessary to spatially study crime (see Hipp & Williams, 2020; Taylor, 2015). Future research will undoubtedly be required to address this issue, but it is not of concern here.
In addition to theoretical differences, the approach to measuring crime based on a spatial context can vary drastically depending on the methods used. Research on where crime occurs have revealed uneven distributions (i.e., non-uniform variability) and largely consistent statistical concentrations (see Andresen, 2011; Kim & Hipp, 2018; Sampson, 2012; Shaw et al., 1929; Weisburd et al., 2012). The latter findings began with the work of Pierce et al. (1988) and Sherman et al. (1989) which discovered that roughly 3% of street addresses accounted for 50% of calls for service. These levels of concentrated were later formulated into the “law of crime concentration” by Weisburd (2015). The law of crime concentration is broadly based on the 80/20 Pareto principle (Pareto, 1909) but also the more detailed levels such as 3-6% of places accounting for 50% of all crime. Research has consistently supported the law of crime concentration and the statical crime ratios have translated from one city to another (Gill et al., 2017). However, the uneven distribution of crime or what can loosely be referred to as the spatial variability of crime is less understood or at least no clear consensus exists on how to best measure it.

To clearly outline going forward the following definition of spatial variability will be used, spatial variability is the measure of crime across a hierarchically ordered geographic space for which values of crime change given their aggregation to a unit. This concept differs from spatial concentration in two major ways. First, spatial concentration is a descriptive measure of how much crime occurs and where relative to the entirety of the examined space. Second, spatial concentration is described statistically rather than spatially. Lorenz curves and Gini coefficients are commonly used to describe levels of crime concentration (see Hipp & Kim, 2017; Mohler et al., 2019). Maps on the
other hand, are a common illustrative tool for communicating spatial variability as they can show hot spots or crime densities.

The nuanced difference between crime concentration and spatial variability is important for advancing crime and place research. Plainly articulating these differences can help guide future scholars and inform them of the methodologies available to them. Because much of the spatial methods used in crime and place research originated from geography criminologists interested in the topic may have difficulty understanding the concepts and results. Providing a clearer understanding of the commonly used methodologies, highlighting new ones, and supporting the use of maps may increase further interest in the area. Growing interest on the topic is also likely to increase future innovation, methodological and theoretical.

**Motivations**

Advancing the understanding of how crime is connected to place through the education and refinement of the concept of spatial variability is the primary motivation for this dissertation. A topic of concern within the crime and place research is the selection of a spatial scale. A common practice is to analyze crime within a single geographic area (i.e., a city) using one or possibly two spatial levels and corresponding units. A typical unit of analysis for much of the recent research has been to analyze crime at the micro-level using units such as street segments (see Malleson et al., 2019; Weisburd et al., 2016). A gap exists though as to what unit(s) should be analyzed, how to analyze them, and how to best communicate the results. Addressing these areas of
concern using the concept of spatial variability are what guide each research study in this dissertation. The following section will briefly overview each study.

The Studies

Following an abstract format, this dissertation has three research studies, each with a focus on the spatial variability of crime. As mentioned above, crime concentration, while a spatial concept, is not a central focus. Instead, each of this dissertation’s studies focus on the methodologies used to measure the spatial variability of crime. The spatial methods used to measure crime variability widely vary with new ones appearing in crime and place literature consistently.

The principal goal of this dissertation is to increase the understanding of the spatial variability of crime and the methodologies used to measure and illustrate it. To do so, a systematic review, a multi-level analysis, and a mapping study are conducted. Each study broadly contributes to the crime and place literature while extending the current knowledge on spatial variability. Particularly, the importance of examining crime across multiple spatial levels is highlighted. Until recently, much of the crime and place research has focused on a single spatial level (e.g., micro, meso, or macro) with a few exceptions examining crime across multiple spatial levels (see Hipp et al., 2020; Hipp & Williams, 2020; Quick, 2019; Schnell et al., 2017; Steenbeek & Weisburd, 2016). This dissertation argues that to better appreciate and illustrate the spatial variability of crime multiple levels of aggregated crime across space must be jointly analyzed. Doing so will also address concerns related to ecological fallacies and the modifiable areal unit problem (see Andresen, 2011; Openshaw, 1984, Robinson, 1950).
Due to recent trends in crime and place research that heavily emphasize spatial concentration there is a knowledge gap concerning spatial variability. These two research interests are diverging into their own perspectives with rapid advancements taking place for each. This dissertation is presented with the timely opportunity to explore much of the recent empirical work and present new methods for spatially analyzing crime variability. A few issues are prominent from the lack of a consensus regarding the spatial variability of crime. First, to the author’s knowledge, no consensus exists on what methodologies are used or should be used to study the phenomenon. Second, crime and place researchers too often choose to examine crime aggregated at a single spatial level versus using a more appropriate multi-level approach. Lastly, innovations in crime mapping appeared to have stalled despite significant advancements outside the field of criminology. These issues are the basis of the three research studies that make up this dissertation. Each research study is briefly discussed below.

Research Study One

The first study in this dissertation is guided by the research question, what methodologies are used to examine the spatial variability of crime and what are their outcomes? Commonly, cluster-based tests such as Moran’s I and local indicators of spatial autocorrelation (e.g., local Moran’s I, Getis-Ord G$_i$ and G$_i^*$) are used to examine spatial variability. However, other possibilities exist, and the application of those tests can differ. For example, typical methodologies used in recent crime and place research often test for spatial autocorrelation at the micro-level using crime estimates aggregated to a micro-unit such as street segments (Kim & Hipp, 2018; Weisburd et al., 2012). Other research focuses on spatial variability at the meso-level where neighborhoods or other
similarly sized areas are of interest (Bursik, 1988; Jones & Pridemore, 2019; Sampson, 2012). An abundance of other nuanced information is also important for formulating an in-depth understanding of the methodologies used for this type of research.

The uniqueness of selected methodologies and other relevant information are captured using a systematic review. Extensive protocols for the systematic review are based on the Campbell Collaboration. This research question is answered by examining many factors from relevant research that measures the spatial variability of crime. To help guide the research only studies from the past decade (2010-2019) are analyzed. This period, which is conveniently and deliberately chosen, includes David Weisburd’s seminal piece on the “law of crime concentration” (Weisburd, 2015). Weisburd’s (2015) introduction of this “law” marks a renewed interest in crime and place research, particularly one that emphasizes the analysis of micro-units. In addition, new advancements in computer and GIS technologies have allowed for continual improvements of how crime is analyzed spatially. Ultimately, the goal of this study is to identify trends for the methodologies used to the measure the spatial variability of crime.

**Research Study Two**

The second research question is, *how much of the total spatial variability of robbery incidents can be attributed to census blocks, census tracts, and city-wide for eight U.S. cities and do these estimates differ between cities?* An abundance of research has observed that the greatest amount of spatial variability occurs at the micro-level (Kim & Hipp, 2018; Malleson et al., 2019; Weisburd et al., 2016) with modest variation occurring at larger spatial levels (Baumer et al., 2012; Hipp & Williams, 2020; Schnell et
Crime and place research often highlight the importance of spatial levels while rarely addressing the multi-level interactions between the levels. More so, research is often restricted to within-city analyses even those that use multi-level approaches (see Hipp et al., 2020; Quick, 2019; Weisburd, 2015).

Using a similar approach as Schnell et al. (2017) and Steenbeek and Weisburd (2016), with the addition of between-city comparisons, this study explores how the estimates of spatial variability for robbery differ within- and between-cities across two spatial levels. Like recent studies, the importance of micro-places is highlighted as they provide a better understanding of crime variability and concentration given their presence in larger geographic spaces. Much attention is paid to the importance of city-level differences and how the variability of robbery may not be uniform for U.S. cities.

Multiple analyses were conducted to answer this research question. Descriptive analyses such as tests of statistical concentration were used to examine the spatial distribution of robbery for each of the cities. The spatial variability attributed to blocks and tracts within each city was calculated using variance partitioning with multi-level negative binomial models. These models allow for between-city comparisons. Sensitivity analyses were also conducted to test various methods for estimating the variance of robbery incidents.

**Research Study Three**

The third study is guided by the research question, *how are maps currently being used and what are best practices to illustrate the spatial variability of crime?* Two research goals also frame this study. One, discuss and present best practices for
communicating the spatial variability of crime through mapping. Two, promote the continued use of maps in criminological research by highlighting innovative mapping techniques. Cartography in research is not an unusual concept, nor is crime mapping for that matter (Chainey, 2021; Chainey & Ratcliffe, 2005; Monmonier, 2018). However, recent trends seem to indicate that academics are less concerned with the continuous advancements being made in cartography (O’Sullivan & Unwin, 2010). It is common to see no maps or maps only used to communicate geographic boundaries rather than more innovative uses such as dynamic maps which include interactive maps. Journal restrictions are partly to blame for the simplicity in map design (O’Sullivan & Unwin, 2010). Additionally, a push towards advanced quantitative measures rather than visual techniques such as maps also may be a contributing factor for their reduced use.

In this research study, an argument is presented that, combined with the recent attention on spatial methods, maps still play a key role in communicating results. Particularly, in studies of spatial variability, a multi-level concept, maps can help communicate the importance of each spatial level given their larger geographic context. Maps to be included within journals (paper or online) and as external appendices to articles were created. A variety of methods are discussed on creating interactive maps and multiple examples are showcased to encourage academic interest for their continued use. Each map is also in-part, a method of effectively communicating estimates of the spatial variability of crime.
CHAPTER 2

LITERATURE REVIEW

Unlike traditional dissertation literature reviews that heavily focus on theory, this chapter discusses the advantages of including a spatial component for crime research. An in-depth review of methodologies used in crime and place research also follows. A note on theory is necessary before continuing, though. The theories used in crime and place research are certainly important, but the methodological choices made in research are rarely theoretically informed. Explicitly, the opportunity theories and social disorganization theory only familiarize the researcher to the importance of place versus how to measure that importance. Therefore, the subsequent sections of this chapter only discuss the methodological choices necessary when conducting crime and place research. The “selecting a unit of analysis” section discusses the importance of analyzing crime at different spatial levels and units. Next, crime maps are discussed in the “mapping crime” section where the history, data, and new design techniques are highlighted. The final section, “spatially analyzing crime” reviews the differences between crime concentration and the spatial variability of crime. Spatial tests for autocorrelation, among others, are also discussed with contextual examples from relevant literature.

Human behavior, including criminal behavior, occurs somewhere. Somewhere can be a measurable location that is increasingly being captured within crime data in the
form of XY coordinates or some other similar variant. Extensive research has discovered that crime is not a random occurrence or equally distributed across space (Chainey, 2021; Weisburd et al., 2016). In fact, crime is highly concentrated. Research has also observed that the variability of crime is dependent on the geographic unit being examined (Schnitt et al., 2017; Steenbeek & Weisburd, 2016). For instance, when examined at multiple spatial levels, the smaller or more micro-level, will account for the most variance of total crime when compared to larger spatial levels. Representations of micro-units can include single addresses, street segments, and census blocks among others. Micro-level spatial units likely account for the majority of crime variance given they are where the “action” of the crime occurs. For example, a single street segment with numerous bars also has numerous late-night physical assaults. When aggregated to a larger spatial level such as neighborhoods, the micro-level processes occurring can be “drowned” out or perhaps over-amplified by nearby high-crime streets as well. Viewing crime beyond a single microcosm is important for many reasons that are detailed in the subsequent sections.

**Selecting A Unit of Analysis**

The challenge of selecting a unit of analysis is not unique to crime and place research. Geographers have long been plagued by the choice of which spatial level and unit are the most appropriate for their research question(s) (Wong, 2009). The type of data available can help direct the decision, but many times it is not clear what the most suitable decision is. Historically, units of analysis were chosen based on convenience. Neighborhoods were often used as a spatial unit during the Chicago School because they were readily available boundaries for access (Shaw & McKay, 1942). Before the
computer and spatially tailored software, the complication or impossibility of conducting spatial analysis by hand also shaped unit choice.

Perhaps the most important issue of selecting a unit of analysis is the dealing with aggregation bias (Woolredge, 2002). Aggregation bias is more comprehensive term that includes the ecological fallacy (Robinson, 1950) and the modifiable areal unit problem (MAUP hereafter; Openshaw, 1984). Both are examples of using aggregated data to make inferences about individuals or areas smaller in size than what was measured or used for analysis. An example of an ecological fallacy would be to label all individuals in a high-crime neighborhood as criminals. The geographic fallacy of MAUP is more nuanced in that researchers must be aware of the endless and seemingly arbitrary demarcations of geographic boundaries commonly used that can affect statistical outcomes (Openshaw, 1984; Wong, 2009). For example, census tracts are often used as a proxy for neighborhoods. Yet, they certainly do not align with the traditional sense of many neighborhoods, nor do they change at a pace (the U.S. census is conducted every 10 years) that keeps up with rapid development which can greatly impact neighborhoods.

Aggregation bias also occurs when only examining crime at a single spatial level. Andresen (2011) addressed this issue when he compared crime rates for census tracts and dissemination areas. Each spatial unit was used to aggregate crime data by attributing a count of crime per unit. Tests for spatial clustering were conducted for each unit to examine any differences. Though the results between the two units were mostly similar, the observed differences highlight how two geographic boundaries using the same data can have different outcomes. If only a single spatial unit had been examined, any
conclusions drawn could have glossed over hidden spatial heterogeneity at more localized levels.

The choice to spatially analyze crime data using a single unit of analysis is commonly made, mostly due to data availability. The effect of doing so becomes pronounced when only examining crime at meso or macro levels. Doing so invites the possibility of exaggerating the variability and concentration of crime while ignoring local processes which are more fitting to the behaviors of individuals. To provide context, imagine a high crime neighborhood. Only analyzing crime using this geographic unit will likely produce overestimation of how “dangerous” or crime-ridden the neighborhood is. In reality, the neighborhood contains many street segments that have no crime with a few that are responsible for most of it. In fact, a few street addresses that are clustered together and have high crime can make it seem like the entire neighborhood is full of crime.

The possibility of overestimating crime in the opposite direction (micro to macro) can also occur. When using hot spots to examine high crime locations in a city, single crime incidents are interpolated into a non-structured shape that can “grow” dependent on certain factors. For instance, specific distance bands or spatial weights can be applied that will create outcomes with markedly different hot spots. In some cases, a few crime incidents can cluster together creating a hot spot that will “spillover” into neighboring areas where no crime occurred.

With the above-mentioned issues concerning selecting a unit of analysis it is tempting to ask what the “best” spatial level or unit is. Malleson et al. (2019), attempted...
to find the most appropriate spatial scale regarding crime patterns. Their findings suggest that one singular unit likely does not exist, and the choice unit will depend on the type of crime being analyzed. The researchers also suggest that increasing the use of smaller spatial units such as street segments to analyze crime is favorable. Doing so provides better estimates of spatial heterogeneity that occur within the larger areas containing the streets such as neighborhoods. In this approach, crime concentration can be observed at very local levels while also understanding the spatial variability of crime within larger spatial units.

Data availability combined with the research question at hand are the predominant drivers behind selecting a unit of analysis. However, when possible, the best approach is to analyze crime data across multiple spatial levels (see Andresen, 2011). Doing so reduces issues related to aggregation bias and provide better representations of how crime varies across a larger geographic area. The nested properties of geographic boundaries commonly used for crime and place research are also prime candidates for multi-level analysis (i.e., census blocks nest in block groups, which nest in tracts). Even when units, such as street segments, do not nest perfectly within others, many techniques exist such as “clipping functions” which only capture data within the selected boundaries. A growing amount of research is beginning to recognize the importance of spatially analyzing crime across multiple levels rather than relying on a single unit or arguing the importance of one unit over another. To fully understand how crime is concentrated and varies across larger geographic areas such as cities, utilizing the strengths of multiple spatial levels and units is recommended. Doing so will help shape future discourse on the topic by guiding relevant theory and policy.
The incorporation of theory has also influenced the selection of a unit of analysis. But, as mentioned above, the current crime and place theories commonly used do not inform specific methodological choice. Instead, the theories simply imply which spatial level *could* be analyzed. The choice of a spatial unit is not clear either. From a macro to micro scale, the crime and place theories range from routine activities (macro), crime pattern theory (meso), social disorganization (meso), and rational choice (micro). Though each theory tends to focus on understanding crime as a product of the socio-physical world across varying geographic scales they are not always appropriately applied. Taylor (2015) notes that a common misapplication occurs with the use of routine activities for multiple levels of spatial scale. Making this mistake can lead to the misidentification of results and lead to incorrect inferences. As of late, a noticeable shift from larger spatial units to micro-units has occurred in much of the crime and place research (Hipp & Williams, 2020; Weisburd et al., 2012). While micro-units are often more appropriate for several reasons, the decision to move from larger to smaller units is not always explained or deduced from theory.

**Mapping Crime**

The uniqueness of spatial variability is that it can be illustrated using maps. The use of maps for studying crime predates the establishment of the field of criminology (see Balbi & Guerry, 1829; Guerry, 1833; Quetelet, 1831 [1984]). When designed well, maps can easily and effectively communicate crime data. Conversely, like other visualization types, maps can be deceiving about the information they display (O’Sullivan & Unwin, 2010; Monmonier, 2018). Careful consideration is required about how maps are designed
and the data that are being used to create the map. A variety of techniques are available for researchers to create maps, some of which are discussed here.

Creating Maps

Historically, creating maps was a time-intensive process completed by hand on paper. Today, computers allow access to user-friendly software designed exclusively for creating maps which can take very little time or mapping knowledge. With new innovations for making maps come new problems and historical ones with new considerations. While cartographic theory extensively outlines the history, use, and design of maps the following sections will be restricted to how maps and crime and place research connect.

Data

Spatial representations of geographic places are part of the vector data model. Vector data are made up of points, lines, and polygons. Each of these data types are important for crime and place research and examples are provided for each. Point data is the most common type as it is simply observed crime incidents that have some pair of coordinates. Point data are the basis of many spatial statistics and how crime and place research aggregates to certain spatial units. Line data are ordered sequences of points that are connected. Street segments are an example of line data. Polygons, or area data, are points that are connected by lines to form polygons. Census blocks, tracts, and neighborhoods are polygon data. Another spatial object is raster data which are made up of cells with associated values. Raster data are not commonly used in crime and place research.
For crime to be mapped it must contain a pair of coordinates. Coordinates can then be placed into a geographic information system (much like a typical database but with the coordinate information) and mapped against some backdrop. The backdrop can be a city for example. Contained within the city, lines and polygons can also be mapped. For example, streets, rivers, parks, police beats, etc., can all be mapped for additional context. The combination of the spatial object types can be beneficial for the user or detrimental dependent on design features. Additionally, consideration must be taken regarding the quality of the data used for the map. Particularly, the crime data.

A few well-known limitations exist about crime data. First, official crime data are only those incidents which were reported, captured, and recorded by law enforcement. Second, for privacy concerns, crime data are often “shifted” away from the original location they were recorded (Chainey & Ratcliffe, 2005). For example, if a crime occurred at location ‘A’ and was recorded at that location, a shifting process will be applied to move the point 50 feet in a random direction to protect the privacy of potential victims. Often these shifting processes are not made public as they could potentially be reversed back into the original positions. Nonetheless, this is a well-known tradeoff for obtaining public crime data. Lastly, in addition to the deliberately shifted data, the original process for recording an incident is not always uniform. For example, if a crime occurs at an intersection or unknown location, the responding officer may attribute a nearby location to the incident versus recording the actual location.

The accuracy of crime data has long been questioned with recent research suggesting errors in the data may impact micro-level spatial analyses more so than meso- or macro-level ones (Buil-Gil et al., 2021). Micro-level crime and place research is the
most vulnerable because the crime data are often not aggregated to larger areas which can reduce estimation biases based on data errors. At the micro-level, small errors, or deliberate ones such as shifted data are likely to greatly influence any estimate of crime at that scale due to their much smaller size. While some of these issues are ongoing, each highlight the importance of proper data cleaning before any spatial analysis or mapping is attempted.

**Projections.** When mapping any data, understanding how projections work is crucial. Not choosing the appropriate projection can greatly distort a map leading to user disinflation and incorrect inferences about the data (Peterson, 2021). Simply, projections allow for spatial data such as crime incidents to be integrated with other geographic information and then mapped. Coordinate systems are the basis of all projections, and they can be split into two types: geographic and projected. A geographic coordinate system is a three-dimensional arrangement for the surface of the Earth using lines of latitude and longitude. A projected coordinate system is how the 3D Earth is transformed into a 2D surface that can be mapped on. There are many types of projections but rarely are they discussed in the crime and place literature. One reason is the scale of analysis for many studies is very local (city level) relative to the geographic area covered by projections and they need not be considered. However, for larger-scale studies data can become distorted if the proper projections are not used. Peterson (2021) notes that while most researchers could not be bothered with projections, studies across large geographic areas will undoubtedly run into projections issues. While the current state of crime and place research is primarily limited to single cities, future research may
expand to larger geographic areas where a greater understanding of projections will be required.

**Design**

Maps are visual representations of information. The design of maps can significantly dictate what the map consumer interprets as important or not. There are many factors to consider when designing maps that are beyond the purview of this dissertation (see Brewer, 2016; Chainey & Ratcliffe, 2005; Monmonier, 2018; Peterson, 2021). For this discussion, two design aspects are highlighted. These are map color and dynamic capabilities. These two were chosen for further discussion because one is a historical design element, and the other is a novel approach for creating maps.

To communicate differences of information compiled in a map, color has historically been a go-to design feature. The grey scale shaded regions of France in the crime maps by Balbi and Guerry (1829) are one such example. The computer-generated color-coded hot spot maps of today are another. Color, which is comprised of hue, value, and chroma can be a powerful tool of communication (see Brewer, 2016 for an in-depth explanation on color). Color can have different meanings to different people and can be incorrectly applied more easily than it can be correctly. When combined with non-equal geographic sizes, color can become very misleading. For example, two neighboring areas that are shaded similar colors but of vastly different sizes can become confusing as to their importance. Additionally, color scales with too much variance are difficult for the user to discern. Though many color design options are available to the map creator, it is
often recommended to go simple and stick with little color variation (O’Sullivan & Unwin, 2010).

The second design element highlighted for this review is a product of more recent mapping capabilities. Dynamic maps are a comprehensive term for maps that are interactive rather than static. These types of maps can include zoom features, the ability to turn layers on and off, and linking and brushing among others. Dynamic maps can be hosted through the web or included within documents using specific programming language (see Lovelace et al., 2019). The benefit of these types of maps are the ability for the user to directly interact with the data. For example, a linking and brushing feature allows the user to select certain regions on the map which will then correspond to an accompanying statistical graph such as a scatterplot (O’sullivan & Unwin, 2010). The capabilities of dynamic maps are continuously advancing as computer technology, data availability, and the general interest of visual data increases. Though dynamic maps are currently used to illustrate crime data, rarely are they created for academic purposes. Journal limitations are a primary reason for the bland looking maps commonly witnessed in the crime and place research. However, as noted by O’Sullivan and Unwin (2010) a lack of academic interest for the growing mapping capabilities may also be to blame. Whatever the reason, a missed opportunity for representing crime data in an innovative manner is occurring and needs to be addressed.

**Analyzing Crime Using a Geographic Lens**

Many techniques are available for analyzing crime using a geographic lens. The techniques can be separated into two types of measures: crime concentration and spatial
variability. Both measures have flourished recently as GIS functionality has increased and become more accessible along with the development of new spatial statistics (e.g., see Anselin, 1988, 1995; Cressie, 1993; Getis & Ord, 1992; Ord & Getis, 1995). However, as in the case of crime concentration, not all methods are new, but rather, new takes on old methods (see Gini, 1912; Lorenz, 1905). Nonetheless, much of the recent crime and place research can be placed into one or both methodological categories.

Crime Concentration

In introducing the law of crime concentration, Weisburd (2015), highlighted a few notable observations that are often found in crime and place research. The first being that smaller spatial units are necessary to uncover accurate measures of crime concentration. Secondly, when using a micro-level spatial scale, concentrations of crime will be evident for a small proportion of the total defined area. The locations with high concentrations of crime will account for much of the total observed crime and the relationship will be temporally stable (see Weisburd et al, 2012). Particularly, the use of street segments in research reveals that only a very small percentage of the segments will contain crime occurrences as crime is a rare phenomenon and not equally distributed across space. An area, or street segment for this example, may be surrounded by other street segments that contain no crime at all.

Much of the foundation for the law of crime concentration came from the seminal research of crime across Seattle, WA, by Weisburd and colleagues (2012). In their study, they examined the longitudinal stability of crime at the street segment. They found that crime is very stable across time (between 1989 and 2004) and is concentrated at a small
percentage of street segments. For each year examined in the study, approximately 4.7% to 6.1% of street segments accounted for 50% of the crime. This is a similar finding based on earlier research from Sherman et al. (1989) and Sherman and Weisburd (1995) which discussed the concept of crime hot spots and the relative concentration of crime to a few places. While the ratio of crime to place varies by study, generally, 80% of crime can be allocated to 20% of locations across a city. The 80/20 crime rule is the basis of the law of crime concentration and mimics the Pareto principle (Pareto 1909; Rosser et al., 2017). An increasing number of studies have also found evidence that supports the law of crime concentration of which too many exist to list here (see Andresen & Malleson, 2011; Gill et al., 2017; O’Brien, 2019).

Lorenz Curves and the Gini Index

The primary method of measuring crime concentration is to use descriptive techniques. A common practice is to determine the percentage of spatial units that account for 50% and 80% of crime for the study area (see Steenbeek and Weisburd, 2016). A more advanced, yet still relatively simple technique combines the illustrative property of the Lorenz curve while also statistically communicating a numerical summary of inequality via the Gini index. The Lorenz curve and Gini index were developed in the field of economics for studying income inequality (Gini, 1912; Lorenz, 1909). The Lorenz curve is a graphical display that illustrates inequality from a theoretical reference line. The Gini index or coefficient is a numerical summary of the Lorenz curve varying from 0 to 1. Figure 1.1 shows an example of a Lorenz curve (colored red) against a reference line (colored black). The Gini index is calculated as the
proportion of space between the reference line and the Lorenz curve compared to the total space below the reference line.

Figure 2.1. Example Lorenz Curve.

When used to study crime, a zero on the Gini index indicates no concentration and a one indicates perfect concentration of crime. The Lorenz curve and Gini index also provide a good confirmation of the law of crime concentration as the extend its descriptive properties (Eck et al., 2017). In crime and place research the two measures provide visual and quantitative descriptions of the concentration of crime. However, they do not show where the concentration are such as hot spots can on a map. Nor do they help explain the variability of crime across multiple spatial levels.

The use of the Lorenz curve and Gini index also have a few other limitations that limit its ability as a standalone assessment in crime and place research. Mohler et al. (2019) discussed how both estimators can be severely biased when a small N is used. This can be a common occurrence in crime and place research as crime is often aggregated, thus, lowering the sample size. Bernasco and Steenbeek (2017) also
identified a weakness when using the perfect equality reference line of the Lorenz curve as a true comparison to observed crime concentration. In certain situations, places outnumber observed crime. This issue can arise when examining single crime types against micro-places such as street segments. Using the Lorenz curve and Gini index with imbalanced data can lead to biased estimates. The authors addressed this issue by developing a generalized version of the two techniques that replaces the line of perfect equality with a computed line of maximal equality based on the data analyzed.

**Spatial Variability**

Unlike measures of crime concentration, analyzing how crime varies across space allows researchers to understand where crime is occurring and at what amounts per spatial level. A common approach is to use crime maps as visual illustrations of crime variability (see separate discussion in the ‘Mapping Crime’ section) combined with measures of spatial autocorrelation. Where measures of crime concentration are descriptive statistics, spatial variability estimates are statistical outcomes (i.e., crime locations) based on placed-based characteristics such as criminal opportunities. How these observed crime incidents are located throughout space can be measured and mapped using a variety of techniques. Some of the most common techniques are discussed below.

**Hot Spots**

Hot spots are areal clusters of crime relative to the observed crime distribution for the examined area (see Chainey, 2021; Sherman et al., 1989; Sherman & Weisburd, 1995). The use of hot spots has a long history in the crime and place research (see Braga
Depending on the technique used to calculate them and the spatial level examined, hot spots can dramatically differ. A crude technique uses point data (i.e., observed crime incidents) that are aggregated and graduated on a map to account for numerous crime incidents at a single location such as a bar or nightclub (Chainey & Ratcliffe, 2005). Regardless of the technique used, hot spots are simplistic representations of how crime can be place-dependent and vary unequally across space rather than be concentrated in areas. More advanced methods for creating hot spots are discussed in the following three sections.

**Nearest Neighbor Analysis**

Also called average nearest neighbor, nearest neighbor analysis is a distance-based statistic used to determine the spatial dependence of a point pattern (Grekos, 2020). A point pattern can be random, dispersed, or clustered. The null hypothesis for the test statistic is that the observed pattern exhibits complete spatial randomness. By comparing the observed spatial patterning to a theoretical one, expected complete randomness, the test statistic provides a nearest neighbor ratio. A p-value is also calculated to determine the significance of the ratio. However, this measure is highly sensitive to the study area’s size and does not indicate where clustering is occurring. Nearest neighbor analysis only gives a global indication of the presence of clustering, but not where it takes place.
Ripley’s K Function

Like the nearest neighbor analysis, Ripley’s $K$ function is a test of point patterns using a distance measure (Ripley, 1976). For this test, the number of events within a user-defined radius is calculated. The distance defined radius is placed around each point and for each set distance. The total count of “captured” events is then compared to what is expected given that no spatial patterning is evident (Grekousis, 2020). Multiple variations of this test statistic exist, but in principle, each is using radial distance measures to determine whether spatial patterning exists beyond what is expected for the data.

A problem with this method is the likelihood of having edge effects distort the detection of spatial patterning. When crime data from a single city are analyzed, a common issue affecting the analysis is the data being “cut off” by administrative borders (Kim & Hipp, 2018). For example, if a major crime area on the border of the city and a nearby unincorporated area exists, only the city data will be analyzed. The demarcation of administrative or political boundaries does not prohibit crime from occurring in one location versus another. Therefore, edge effects can have a significant impact on spatial analysis. Other physical boundaries such as rivers, parks, and major transportation routes can create edge effects (Kim & Hipp, 2018).

Kernel Density Function

The kernel density function is a test statistic that provides the most familiar-looking hot spot maps. Areas with varying densities of point data and graduated colors are used to map hot spots. Where the nearest neighbor analysis and Ripley’s $K$ function provide estimates, the kernel density function illustrates generally where and how strong the
observed spatial patterns are. However, the strength of the observed spatial patterning is not determined by statistical significance.

To calculate the kernel density function, a grid of cells is generated over the point data. Each cell is then analyzed whereby a “kernel” moves across each cell given a set-distance and calculates weights for each point encountered (Chainey & Ratcliffe, 2005). A kernel refers to a three-dimensional window function that moves across each cell giving higher weights to closer points (Johnson, 2017). A commonly used kernel type is Gaussian influenced but different spatial statistics programs use different kernel functions such as Poisson (Grekousis, 2020). After the weighted distances are calculated each grid cell is given a measure based on its summed weights. The result of the analysis is a smoothed density estimation illustrating instances of higher or lower point occurrence around each cell. While this method of analysis is very common in crime and place research, a few caveats limit its functionality compared to more localized methods (Grekousis, 2020; Johnson, 2017).

Like other global measures used to detect spatial patterning, the kernel density function is limited by cell size and the chosen kernel function (Johnson, 2017). Small variations in the cell size can change the outcome of the analysis. Particularly, the use of large bandwidths for the kernel function to examine each cell are more appropriate for revealing large-scale patterning (Fotheringham et al., 2000). Because the use of kernel density function is common in crime and place research, general guidelines for bandwidth selection exist to help the researcher determine which is best for use (see Chainey & Ratcliffe, 2005). Another issue that exists with the use of this measure is the application of “smoothing” which is also influenced by the selected bandwidth. Chainey and Ratcliffe
(2005) note that the smoothing process can extend over areas where no crime occurred, but due to the estimated density function, it appears crime is more widespread than in reality. Hence, the crime hot spots can exaggerate the distribution of crime. While there is a lot of flexibility in the use of the kernel density function, a more accurate representation and one that provides evidence of statistical significance are indicators of spatial autocorrelation.

**Spatial Autocorrelation**

At its most basic form spatial autocorrelation suggests a nonzero covariance between the values on a random variable for neighboring locations:

\[
\text{Cov}(y_i, y_j) = E(y_i y_j) - E(y_i)E(y_j) \neq 0 \text{ for } i \neq j
\]  

(1)

where \(i, j\) represent locations (Anselin & Bera, 1998; Darmofal, 2015). The null hypothesis for a test of spatial autocorrelation indicates a random distribution of the values on the random variable, i.e., that the locations of \(i\) and \(j\) do not provide evidence of spatial proximity or dependence (Darmofal, 2015).

Spatial randomness is the inverse of spatial autocorrelation. When spatial autocorrelation is present it can be classified into two categories: positive or negative (Harris, 2016). Positive spatial autocorrelation occurs when locations that are similar are close to each other such as two adjacent neighborhoods with high crime rates. Negative spatial autocorrelation is when a pattern of dissimilar (high and low) locations occurs more frequently than true spatial randomness (Fortin & Dale, 2009). A map representing negative spatial autocorrelation would look like a checkerboard (Harris, 2016). However, checkerboard patterns are not visually obvious and are often not discernable from spatial
randomness. More developed measures of detecting spatial autocorrelation are necessary for analysis and are discussed in the following sections.

**Global Patterns.** Global patterns of spatial autocorrelation are estimates of spatial clustering across large geographic units. They illustrate how the data exhibits spatial dependence in its entirety. The identification of clusters does not occur with the use of global spatial statistics, but rather local measures. Global patterns can be analyzed as dichotomous or continuous variables (Darmofal, 2015). An example of a dichotomous variable is whether crime occurred at a certain threshold per community or not. A join count analysis is applicable in this scenario where binary weights are utilized to create the weights matrix. The other method, which will be discussed in detail, is the analysis of continuous-like data such as crime counts. While they are truly not continuous, crime counts are often treated as such. To analyze crime incident data an understanding of the spatial weights matrix and the two more commonly used global measures of spatial autocorrelation is necessary.

**The Spatial Weights Matrix.** In spatial autocorrelation statistics, weight matrices apply to many of the commonly used measures. A weight matrix summarizes the spatial data and any relationships that exist among a variable at one areal unit against its neighbor(s) (Chi & Zhu, 2020; Dubin, 2009). Two types of spatial structures can be used to create a spatial weights matrix. These are contiguity and or distance-based structures (Chi & Zhu, 2020). A contiguity-based structure implies that each areal unit “touches” another, therefore, they are neighbors. Commonly used contiguity structures include the “rook’s case” and “queen’s case”. In a rook case structure, neighbors are defined as spatial units that share a common edge (Darmofal, 2015). A queen case structure defines
neighbors as any spatial unit sharing a common edge or vertex much like in a game of
chess. Anselin (1988) notes that in a queen case structure all spatial units contiguous to \(i\)
are neighbors of \(i\).

The following is a spatial weights matrix where matrix \(W\) contains elements \(w_{ij}\)

\[
W = \begin{pmatrix}
w_{11} & w_{12} & \cdots & w_{1n} \\
w_{21} & w_{22} & \cdots & w_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
w_{n1} & w_{n2} & \cdots & w_{nn}
\end{pmatrix}
\]  

(2)

For neighbor cases in a spatial matrix, a ‘1’ is used for coding based on observation \(i\) and
its neighbor \(j\). A common practice is to row standardize the weights which allows for
easy use in many of the spatial statistic models (Chi & Zhu, 2020). Row standardization
involves summing the total weights per row and dividing across neighbors. The
interpretation of spatial proximity for a unit is easier when row standardization is used.
Other options that can be applied to spatial weight matrices are fixed or variable weights.
Distance measures and functions of the examined variable can also affect how these
matrices are created (Chi & Zhu, 2020).

Many configurations exist for how spatial weights matrices are created and used.
Perhaps, the most important use is for exploratory spatial data analysis and fitting spatial
regression models (Dubin, 2009). Like many spatial statistics, there is difficulty in
selecting the best method for a given research questions. In some instances, theory can
help inform the researcher but as previously discussed, crime and place theories do not
provide such justification. However, selecting which matrix to use can rely on the
research question itself. Chi & Zhu (2020) suggest selecting a matrix that allows for high
spatial autocorrelation for exploratory purposes. This method is used in conjunction with
Moran’s *I*. When using a spatial weights matrix, a common challenge encountered is imprecise data which can lead to “islands” in the data where no neighbor exists. Using distance-based measures can also include too many or too few neighbors. The best practice is to see what best fits the data combined with guidance from prior research or theory.

**Global Moran’s *I***. The Moran’s *I* statistics is a measure used for detecting global spatial dependence and whether the dependence is statistically significant (Moran, 1950). Moran’s *I* statistics is defined as

\[
I = \frac{n}{\sum_{i<j} w_{ij}} \frac{\sum_{i,j} (y_i - \bar{y})(y_j - \bar{y})}{\sum (y_i - \bar{y})^2}
\]

where \(y_i\) and \(y_j\) are the values on the random variable at locations *i* and *j*, \(\bar{y}\) is the mean of the variable of interest, and \(w_{ij}\) is the spatial weight of the link between *i* and *j*. When the values for locations *i* and *j* are more similar or dissimilar, Moran’s *I* is a larger positive or negative value. Weaker neighbor relationships are closer to ‘0’. The theoretical bound for Moran’s *I* is between -1 and 1, with positive correlation between 0 and 1, and negative between -1 and 0. Stronger correlations are closer to the extremes of the bound.

The use of Moran’s *I* is very common with larger areal data and when global trends are detected. When examining an entire city’s crime data, Moran’s *I* can detect spatial clustering and whether the clustering is significant beyond what is expected: spatial randomness (Darmofal, 2015). However, to determine where clusters exist and to detect finer precision regarding spatial heterogeneity, local indicators of spatial
autocorrelation are required. Lastly, a null finding using Moran’s $I$ does not imply the absence of spatial dependence at the local level, thus providing more evidence for the use of local measures (Waller, 2009; Ward & Gleditsch, 2019).

**Geary’s $c$.** Another measure of spatial autocorrelation is Geary’s $c$ statistic (Geary, 1954). Like Moran’s $I$, Geary’s $c$ is used to detect global spatial dependence. The interpretation of the statistic differs though as values closer to 1 imply spatial randomness, greater than 1 imply negative autocorrelation, and values closer to 0 imply spatially positively correlated data (Chi & Zhu, 2020). Because Moran’s $I$ is considered more powerful and less affected by outliers (Geary’s $c$ gives more weight to extreme values), Geary’s $c$ is less commonly used.

**Local Patterns.** Studying the spatial variability of crime will often involve the use of micro-units to detect local spatial patterns (Weisburd et al., 2012). Global measures of spatial autocorrelation can be viewed as a provisional starting point for crime variability research as they do not detect where spatial clusters are located. Localized spatial clusters can be hidden by global models as broad spatial patterns can “wipe” out smaller patterns (Anselin, 1995). Having a single statistic for an entire study area can lead researchers to violate MAUP or committing an ecological fallacy as they may infer from larger spatial units to smaller units incorrectly (Wong, 2009).

Like global measures, local measures of spatial autocorrelation are designed for the use of point data. However, as in the case of street segments, point data can be aggregated to areal or line data (Weisburd et al., 2012). It is common in micro-place research to use street segments as a measure of local spatial similarity. While other
micro-place types exist, they are commonly limited by small N sizes which can make for model misspecification regarding the detection of spatial autocorrelation (Andresen et al., 2020). The two most popular methods for detecting local spatial dependence are discussed below.

**Local Moran’s I.** Developed by Anselin (1995) as a localized version of Moran’s $I$, local indicators for spatial autocorrelation (LISA, hereafter) are used for disaggregating global patterns of spatial autocorrelation. The Local Moran’s $I$ statistic is defined as

$$ I_i = \frac{\Sigma w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{(y_i - \bar{y})^2} $$

where the notation matches the global statistic in (3). For each attribute, $I_i$ measures the extent of significant spatial clustering of high and low values, and detects spatial outliers (Darmofal, 2015; Grekousis, 2020). The sum of $I_i$ for all observations is proportional to Moran’s $I$ (Anselin, 1995). Compared to its global analogous, $I_i$ identifies significant clusters of high-high and low-low values indicating positive spatial autocorrelation. Significant clusters of differing values indicate negative spatial autocorrelation.

A helpful way to visualize and recommended as an intermediary step between global and local tests is the Moran scatterplot. A Moran scatterplot is a quadrat plot where the observed values on the random variable are along the $x$-axis and the weighted average for each observation’s neighboring values are along the $y$-axis (Darmofal, 2015). Local regression (ex. Lowess) can be used to identify possible structural breaks in the data. Additionally, as the possibility of clustering or outliers due to randomness exists, permutation tests are applied (Grekousis, 2020). A typical permutation test is a Monte Carlo simulation (e.g., see Andresen et al., 2020).
**$G_i$ and $G_i^*$**. Another LISA test commonly applied when studying the spatial variability of crime is the $G$ statistic and its variants. The $G_i$ and $G_i^*$ tests are the two most often used in crime and place research, particularly, for hot spot analysis (Chainey & Ratcliffe, 2005). The more frequently used test, $G_i^*$, is discussed here and is defined as

\[
G_{(u_i,v_i)}^* = \frac{\sum_{j=1}^{n} w_{ij}x_j}{\sum_{j=1}^{n} x_j}
\]

(5)

where $G_{(u_i,v_i)}^*$ is the local statistic at location $I$, which has grid coordinates $(u,v)$ and for which a binary weights matrix is used, set to $w_{ij} = 1$ if locations $i$ and $j$ are within a certain distance, $d$, of each other or else $w_{ij} = 0$. (Ord & Getis, 1995). Differing from the Local Moran’s $I$, the $G_i^*$ statistic is interpreted as positive values indicating high-high relationships and negative values indicating low-low relationships. Both relationships are indications of positive spatial autocorrelation. Negatively autocorrelated cases are difficult to detect with this statistic (Darmofal, 2015).

The result of the $G_i^*$ statistic is sensitive to the distance threshold used which in turn affects the spatial weights matrix. Unlike other LISAs, the $G_i^*$ statistic incorporates $i$ in its own neighborhood set (Grekousis, 2020). Like other distance-based measures though, theory and optimization techniques can be used to justify the chosen distance for calculation. One example is the variogram which helps calculate the best distance threshold to use during analysis (Harris, 2016).
CHAPTER 3

HOW DO WE MEASURE THE SPATIAL VARIABILITY OF CRIME? A SYSTEMATIC REVIEW\textsuperscript{1}

\textsuperscript{1} Spencer, M. D., A. M. Lemieux, and A. Mancik. To be submitted to \textit{Journal of Research in Crime and Delinquency}. 
Abstract

Objective
In the last decade (2010-2019) crime and place research has flourished. The spatial variability of crime has attracted recent interest due to its nested properties of spatial homogeneity. To analyze these properties, diverse methods and units of analysis have been utilized, often with little a priori guidance. This study systematically reviewed the relevant literature and reports on the research methods and findings of the spatial variability of crime.

Data/Methods
Systematic review protocols based on the Campbell Collaboration were followed and machine learning software was used to identify studies for inclusion. Methodological trends used to measure the spatial variability of crime were identified.

Results
We identified 11 studies that studied the spatial variability of crime. Our review reveals a lack of cohesiveness across studies regarding the methods and units of analysis used. Despite the range of methodological choices applied to study the phenomenon, all studies reiterated the importance of micro-units.

Conclusions
Analyzing variance across multiple units and spatial scales is becoming more common. However, defining the concept and choosing methods to study the spatial variability of crime is a work-in-progress. Further research is needed to develop this area of research.
Introduction

Rather than theoretical advancement, crime and place research has often focused on advancing the methodologies used to measure where crime occurs (see Hipp, 2016 for an exception). These advancements come in two flavors: statistical measures of crime concentration, and spatial measures of crime variability. The latter presents a more diverse range of spatial applications whereas the former is a descriptive approach such as described by the law of crime concentration (see Weisburd, 2015). It is often assumed that crime is dependent on place and by some measure it varies given certain place characteristics (Brantingham & Brantingham, 1981; Cohen & Felson, 1979). Little thought is given though to how estimates of crime vary due to methodological choices such as unit selection and tests for spatial variability.

Most studies find support for the law of crime concentration (Andresen et al., 2017; Haberman et al., 2017; Sherman et al., 1989; Weisburd, 2015) and more broadly the connection between crime and place (Weisburd et al, 2016). Little is succinctly understood about the salience of crime variability, particularly if estimates translate between cities. For example, crime concentration using the 80/20 ratio and the observation that 50% of crime can be attributed to 3-6% of places roughly translates from one study location to another (see Weisburd et al., 2012). However, depending on the spatial units examined and tests used, crime variability estimates may not be a universally transferable statistic. Because a comprehensive review or unified definition across studies researching the spatial variability of crime does not exist, a systematic review seems appropriate. The primary focus of this systematic review will be on the methodologies used for examining the spatial variability of crime including the selection of units of
analysis. To help frame the study a definition of spatial variability is provided as *the measure of crime across hierarchically ordered geographic space for which values of crime change given their aggregation to a unit.*

**Background: The Spatial Variability of Crime**

The process of spatially analyzing crime has developed greatly over the last few decades. Within this timeframe research has progressed from predominantly analyzing hot spots to the concentration of crime and now the spatial variability of crime (Sherman et al., 1989; Weisburd, 2015). Much of these topics are well defined by the techniques used to study them with the exception being the latter. For example, when studying hot spots or the concentration of crime there are methodologies readily apparent that are foundational to these topics. The same is not true for studying the spatial variability of crime, a phenomenon without a concrete definition even. Instead, due partially to the developing nature of the topic, a diverse array of methodologies exists with minimal clarity on which to use. Further a key component of analyzing the spatial variability of crime is the selection of units. This is an issue that has plagued geographical researchers for decades (Openshaw, 1984; Wong, 2009).

Much of the history of crime and place research has been characterized by neighborhood-level units or micro-units, typically street segments as of recent (Weisburd et al., 2009; Weisburd, 2015). Analyzing multiple units within a single study is not a new concept (see Baumer et al., 2012; Hipp & Williams, 2021). Yet, until recently much of the crime and place research has not done so. More so, the hierarchical organization of spatial units has often been ignored (i.e., not addressing the modifiable areal unit problem) or analyzed separately (i.e., crime concentration research). Driven by the
popularity of Weisburd’s (2015) *Law of Crime Concentration*, research analyzing the spatial variability of crime has begun to gain traction. At present, no systematic gathering of information on these studies exists. Particularly, it is unclear what methodologies are commonly being used to study crime variability and across what units. To the author’s knowledge, there is at present no clarity of these findings from these studies nor how they compare to estimates of crime concentration. Though, given the complexities of performing a meta-analysis on the outcomes of selected studies none was performed. Only ancillary comparisons are made of their findings.

**Methods**

This systematic review will use the Campbell Collaboration as a guide for its methodology. See Appendix A and B for the proposed eligibility check sheet coding protocol.

**Criteria for Inclusion of Studies**

Five criteria were used to determine relevant studies. First, using the previously stated definition of spatial variability, only studies where crime was the dependent variable and those that examined the phenomena were eligible for review. However, spatial variability does not need to be the primary focus as examinations of spatial concentration are also common and performed in parallel. Second, for a study to be included, a spatial methodology must have been applied. That is, the study was contingent on crime data being geo-referenced, thus making traditionally non-spatial methodologies *spatially contextual*. For example, studies were not limited to methods deemed strictly spatial such as spatial regression or indicators of spatial autocorrelation. Third, the units of analysis were not limited. Therefore, research utilizing any
combination of within and between city comparisons across micro, meso, and macro-levels were included. Some examples are provided for context regarding possible spatial unit choices. Examples of micro-level units are census blocks, street segments, and single addresses. Meso-level units are typically representative of neighborhoods and can include block groups, census tracts, community areas, and police beats. Macro-level units are commonly representative of entire cities but can include other large geographic spaces such as counties or states. Among each level is the possibility for researcher defined areas such as grid cells. Any geographic not previously listed did not exclude any study from analysis. Fourth, for this review, crime was an inclusive term defined as a measure of official reported crime incidents, calls for service, and arrests. Fifth, and lastly, the location of or the reporting law enforcement agency were not exclusionary factors.

Search Strategies

Encompassing search strategies were performed to capture literature that meets the eligibility criteria. First, a keyword search was performed using 12 online abstract databases. Additionally, governmental, and nonprofit organization web pages and the online abstracts of articles presented at professional criminology and criminal justice and geography conferences were searched. Second, a forward search was performed for

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2 The following search terms were used: spatial variability AND crime, crime AND place, “placed-based” AND crime, environmental criminology, geocoding AND crime, geography AND crime, “spatio-temporal” AND crime, “hot spots” AND crime, crime distribution, crime mapping.
3 The following 12 databases were searched: Academic Search Complete, Criminal Justice Abstracts, National Criminal Justice Reference Services (NCJRS), Sociological Abstracts, Web of Science Core Collection, Social Science Full Text, Google Scholar, Academic Search Complete, JSTOR, Applied Social Sciences Index and Abstracts, Dissertation Abstracts, C2 SPECTR (The Campbell Collaboration Social, Psychological, Educational and Criminological Trials Register).
5 These conferences include the annual meetings of the American Society of Criminology, Academy of Criminal Justice Sciences, and the American Association of Geographers.
research that has cited the seminal crime and place work of Weisburd (2015). Third, hand
searches were performed of leading journals in the field of criminology and criminal
justice and geography. Google’s h5-index was used to determine what these journals
were. All searches were restricted to the time frame of 2010-2019. This time frame was
selected because it spans roughly equal time before and after Weisburd’s (2015) work
and presentation on the law of crime concentration. The law of crime concentration
served as a major rejuvenation of research focused on place, particularly research
focusing on micro-units of analysis (see Eck et al., 2017). It is also during this time frame
that crime and place research greatly expanded in scope and methodological
sophistication.

After completing the initial searches, a total of 535 studies were identified as
potentially eligible studies. That is, these 535 studies were deemed to be relevant but not
thoroughly screened for inclusion as part of this study’s analysis. To aid the process of
screening abstracts an open-source machine learning software called ASReview was used
(see van de Schoot et al., 2021). This software was developed to expedite the amount of
time spent screening abstracts. Through a process of varying machine learning algorithms
that can be expressed (the Naïve Bayes algorithm was used for this study), the researcher
is able to continuously train the software by categorizing studies as relevant or irrelevant.
Before the screening, a researcher-defined stopping point was created to determine when

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6 These journals are as follows: Criminology, Criminology & Public Policy, Justice Quarterly, Journal of
Research in Crime and Delinquency, Journal of Experimental Criminology, Journal of Criminal Justice,
British Journal of Criminology, Journal of Quantitative Criminology, Crime & Delinquency, and Criminal
Justice and Behavior. These journals are listed in the top 10 according to Google’s h5-index from 2015-
2019 Criminology, Criminal Law & Policing. Progress in Human Geography, Applied Geography, and the
Journal of Economic Geography were also searched. These are the top 3 according to Google’s h5-index
for Geography and Cartography.
the screening process would cease. The stopping point was defined as \( N / 10 \) where, after ~54 (10%) consecutive studies were categorized as irrelevant the screening process halted. This threshold was chosen because it matches the approximate error rate of humans reviewing abstracts for a systematic review (see Wang et al., 2020). Using this process, a total of 15 relevant studies were identified. The 15 studies were then fully screened and further reduced to 11 eligible studies. The four studies that were dropped, while methodologically interesting, did not explicitly test the spatial variability of crime as defined by this study. Figure 3.1 illustrates the flowchart of the search and screening processes. Approximately 32% (172 of 535) of the eligible abstracts were reviewed using ASReview before the screening was halted. The remaining 68% (363 of 535) of abstracts were not reviewed as deemed unnecessary based on the defined stopping point.

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7 At present, no definitive stopping point using this software or others like it has been studied. Three options exist: predetermined (screen only a set % of all studies); data-driven (stop after X irrelevant studies consecutively); and time-based (stop after a set time). Visit https://asreview.nl/blog/asreview-class-101/#stop-screening for more information on using the software.

8 Despite being closely related to the topic these four studies were ultimately not selected for inclusion as they did not satisfy the current definition of spatial variability offered by this study. In the future, refinement of the concept may lead to these studies being considered fully relevant. Nonetheless, each of these four studies provided relevant information and offered unique methodological perspectives. The studies are (Boessen & Hipp, 2015; Hipp et al., 2017; Lee et al., 2014; Malleson et al., 2019)
Findings

Key features of each included study were examined. These include: the spatial methodology used, spatial unit of analysis, type of crime examined, and relevant findings regarding levels of spatial variability. Other features examined include authorship, location examined, crime incident sample size, years examined, and journal among others.

Table 3.1 presents the basic characteristics of the 11 eligible studies. Over two-thirds (63.7%) of the studies examined locations in the United States or Canada. Of the locations examined in North America, two cities were the subject of two studies each: Boston, MA and Vancouver, BC. Two studies examined locations in Europe and two in Brazil. Within each study, the cities, or metropolitan areas examined had populations >300,000. A few areas of examination (Campinas and Recife, Brazil and Chicago, IL) had over 1,000,000 residents. Regarding crime, most studies (63.6%) analyzed multiple crime types, often including only violent crimes. Of the studies which analyzed a single
crime type, each type is violent (e.g., residential burglary, homicide, robbery, and arson). Almost all studies (45.5% each category) had sample sizes < 10,000 or between 10,000 and 999,999. One study analyzed more than 1,000,000 crime incidents. A single study analyzed crime using data from one year and the majority analyzed data spanning multiple years averaging five years. Most studies used multi-level models (54.5%) with the remaining using point-pattern tests or spatial regression. Concerning the concentration of crime, approximately half did and did not analyze levels of concentration such as how many units account for some ratio of crime.

Table 3.1 Key characteristics analyzed, N = 11

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>N</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Country</td>
<td></td>
<td></td>
</tr>
<tr>
<td>United States</td>
<td>4</td>
<td>36.4</td>
</tr>
<tr>
<td>Canada</td>
<td>3</td>
<td>27.3</td>
</tr>
<tr>
<td>Brazil</td>
<td>2</td>
<td>18.2</td>
</tr>
<tr>
<td>Netherlands</td>
<td>1</td>
<td>9.0</td>
</tr>
<tr>
<td>Sweden</td>
<td>1</td>
<td>9.0</td>
</tr>
<tr>
<td>Crime</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single Type</td>
<td>4</td>
<td>36.4</td>
</tr>
<tr>
<td>Multiple Types</td>
<td>7</td>
<td>63.6</td>
</tr>
<tr>
<td>Sample Size</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;10,000</td>
<td>5</td>
<td>45.5</td>
</tr>
<tr>
<td>10,001-999,999</td>
<td>5</td>
<td>45.5</td>
</tr>
<tr>
<td>&gt;1,000,000</td>
<td>1</td>
<td>9.0</td>
</tr>
<tr>
<td>Years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-3</td>
<td>4</td>
<td>36.4</td>
</tr>
<tr>
<td>4-9</td>
<td>6</td>
<td>54.5</td>
</tr>
<tr>
<td>&gt;10</td>
<td>1</td>
<td>9.1</td>
</tr>
<tr>
<td>Methodology</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Point-Pattern Test</td>
<td>4</td>
<td>36.4</td>
</tr>
<tr>
<td>Spatial Regression</td>
<td>1</td>
<td>9.1</td>
</tr>
<tr>
<td>Multi-level Model</td>
<td>6</td>
<td>54.5</td>
</tr>
<tr>
<td>Concentration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Analyzed</td>
<td>5</td>
<td>45.5</td>
</tr>
<tr>
<td>Not analyzed</td>
<td>6</td>
<td>54.5</td>
</tr>
</tbody>
</table>

Also assessed (not included in tables) were the authors, journal, year published, and use of publicly accessible data. Across the 11 studies, there are 18 authors and half were at the time of publication U.S. based. The rest of the authors were from Australia.

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9 O'Brien and Winship (2017) analyzed 311 reports and 911 dispatches. The samples for each type were 369,172 and 1,673,908 respectively.
Among the authors, two were involved in multiple studies: Daniel T. O’Brien (2x; twice as first author, once as sole) and Martin A. Andresen (4x; once as first author). Eight of the studies were published in journals from the field of criminology, two in geography, and one in the broad domain of social science. Of those published in criminological outlets, four were published in the *Journal of Quantitative Criminology* and two in the *Journal of Research in Crime and Delinquency*. No other publications came from the same journals. Three of the four studies published in *Journal of Quantitative Criminology* were in the same volume and the other in the prior volume.\(^{10}\) Of the 11 studies, all but one (published in 2011) were published after 2015 with four in 2017 and four in 2019. The use of openly accessible data was also quite common with 45.5% of studies doing so.

Of particular importance to this systematic review is the scope of spatial units of analysis across research on the topic. Table 3.2 presents the micro- and meso-level units examined in each study.\(^{11}\) No study examined units beyond what is geographically considered meso-level. It was common for multiple units at each level to be analyzed. The most common unit analyzed was street segments \((n = 8)\) and the least common was grid cells and units that are not easily transferable to U.S. census units (see de Melo et al., 2015; Gerell, 2017). Tracts \((n = 6)\) were another commonly examined unit. There is a large difference between the number of micro- and meso-units analyzed across the studies. Of the 14 types of micro-units examined, 11 included more than 10,000 units. Of

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\(^{10}\) Volume 33 of the *Journal of Quantitative Criminology* had four issues with many studies covering crime and place focused topics. Issue 3 of volume 33 was a special issue titled “The Law of Crime Concentration at Places”.

\(^{11}\) Across the studies, units with the same name but different meanings were used (i.e., dissemination areas). In each case, the study clearly compared these units to recognizable units in the United States. These comparisons guided the categorization as micro- or meso-level units.
the 19 types of meso-units examined, 13 included less than 200 units. All studies assessed the spatial variability of crime using two units of analysis, nine used three units, and two used four units. While four units were used in the models by Schnell et al. (2017) and Steenbeek and Weisburd (2016) only three levels represented spatial units; the other level represented a time component.

Table 3.2 Spatial units by study

<table>
<thead>
<tr>
<th>Study</th>
<th>Micro (N)</th>
<th>Meso (N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Andresen &amp; Malleson (2011)</td>
<td>Street segments (11,730); Dissemination areas (1,011)</td>
<td>Tracts (110)</td>
</tr>
<tr>
<td>de Melo et al. (2015)</td>
<td>Street segments (49,173)</td>
<td>Ponderation areas (36); Tracts (1,749)</td>
</tr>
<tr>
<td>Gerell (2017)</td>
<td>Thiessen polygons (952)</td>
<td>Sub-districts (136); Small area statistics areas (391)</td>
</tr>
<tr>
<td>Hodkinson &amp; Andresen (2019)</td>
<td>Street segments (18,445)</td>
<td>Neighborhoods (22); Tracts (117); Dissemination areas (991)</td>
</tr>
<tr>
<td>O’Brien (2019)</td>
<td>Addresses (98,355); Street segments (13,048)</td>
<td>Tracts (178)</td>
</tr>
<tr>
<td>O’Brien &amp; Winship (2017)</td>
<td>Addresses (123,265); Street segments (13,767)</td>
<td>Tracts (178)</td>
</tr>
<tr>
<td>Pereira et al. (2017)</td>
<td>Street segments (31,777)</td>
<td>Tracts (1,854)</td>
</tr>
<tr>
<td>Quick (2019)</td>
<td>Dissemination areas (656)</td>
<td>Police patrol zones (18); Electoral wards (25); Neighborhoods (97)</td>
</tr>
<tr>
<td>Schnell et al. (2017)</td>
<td>Street segments (41,926)</td>
<td>Community areas (76); Neighborhoods (342)</td>
</tr>
<tr>
<td>Smith &amp; Sandoval (2019)</td>
<td>250-meter grid cells (2,922)</td>
<td>500-meter grid cells (777)</td>
</tr>
<tr>
<td>Steenbeek &amp; Weisburd (2016)</td>
<td>Street segments (15,527)</td>
<td>Districts (44); Neighborhoods (114)</td>
</tr>
</tbody>
</table>

The primary type of methodology applied by each study is of central concern to this review. The analyses across the studies are presented in Table 3.3 by study. Among
the studies which utilized multi-level models there is some diversity of the chosen model. A Bayesian approach, count model, and a nested Gini coefficient model were used once.\textsuperscript{12} Three other studies used linear mixed models with one being a quasi-replication of another (see Schnell et al., 2017; Steenbeek & Weisburd, 2016). Of the studies which analyzed the spatial variability of crime using a point-pattern test, all four used Andresen’s $S$-index (see Andresen, 2009). Of note, in each of the studies using this method, the creator of the statistic was an author. Lastly, of a more traditionally spatial method, a single study used a spatial regression model; specifically, spatial lag and geographically weighted regression models.

Table 3.3 Methodological Analysis by Type

<table>
<thead>
<tr>
<th>Multi-Level Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gerell (2017)</td>
</tr>
<tr>
<td>O’Brien &amp; Winship (2017)</td>
</tr>
<tr>
<td>Quick (2019)</td>
</tr>
<tr>
<td>Schnell et al. (2017)</td>
</tr>
<tr>
<td>Steenbeek &amp; Weisburd (2016)</td>
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<table>
<thead>
<tr>
<th>Point-Pattern Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Andresen &amp; Malleson (2011)</td>
</tr>
<tr>
<td>de Melo et al. (2015)</td>
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<tr>
<td>Hodgkinson &amp; Andresen (2019)</td>
</tr>
<tr>
<td>Pereira et al. (2017)</td>
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</table>

<table>
<thead>
<tr>
<th>Spatial Regression</th>
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</thead>
<tbody>
<tr>
<td>Smith &amp; Sandoval (2019)</td>
</tr>
</tbody>
</table>

\textsuperscript{12} The Gini coefficient is a measure of inequality (Gini, 1912) and commonly used as a descriptive measure of crime concentration (Bernasco & Steenbeek, 2017; Hipp & Kim, 2017; Mohler et al., 2017). Alone, the Gini coefficient would not satisfy the requirement of testing for spatial variability. However, O’Brien (2019) applied a nested use of the coefficient that aims to capture concentrations of crime across multiple geographic scales.
Lastly, of ancillary importance to this review were the findings of each study. Due to the complexities of comparing variance estimates originating from different methodological choices and across varying geographic units of analysis for each study, only the general findings are discussed. Across all studies, the largest share of the spatial variability of crime can be attributed to micro-units of analysis (most often street segments) regardless of how many other units were examined. The units within higher-order geographic scales, often representing neighborhoods, explained the other largest shares of variance.

A few caveats exist though regarding the latter statement and how important these larger units were for explaining variability. In the case of Smith and Sandoval (2019), raster grids were used as units. Like the other studies which used administratively defined units, the smallest unit offered the greatest accuracy for examining local spatial variability. However, their larger unit provided more robust estimates for their models. Gerell (2017) observed that little difference existed between large and medium-sized units, but the smallest units were the most important. O’Brien and Winship (2017) found that 95-99% of the variance was attributed to the micro-unit (addresses).

The results from the three previously described studies contrast with the findings from Schnell et al. (2017) and Steenbeek and Weisburd (2016) which found more support for the importance of meso-units. For example, Schnell et al. (2017) observed that on average 59% of the variance of violent crime was attributed to the micro-unit while larger units were responsible for the remaining 41%. These estimates are similar to Steenbeek and Weisburd’s (2016) findings (average of 62% for micro-units and 38% for higher-order units). Despite the nuanced differences of methodological choice which influenced
how variance was reported for each unit, smaller units (often street segments) were the
greatest indicator for levels of crime variability.

The importance of micro-units is an un-surprising finding given micro-units have
been widely discussed and advocated for use in recent years (see Bernasco & Steenbeek,
2017; Oberwittler & Wikström, 2009). Yet, careful consideration must be taken when
interpreting results using micro-units as they often far exceed the number of crimes being
analyzed, resulting in artificial inflation of concentration and variability. This realization
suggests that the statistical methods rather than units of analysis used may be a more
fertile ground regarding their impact on research findings.

Discussion and Conclusions

The importance of analyzing geographic data across multiple scales and units
gained traction when Openshaw (1984) coined the term modifiable areal unit problem
(MAUP). This term addresses the issue of research foci being too narrow or broad; one,
that disregards spatial trends above and below the unit being examined. While crime and
place research has flourished since the hot spots research of the 1990s to crime
concentration research of the mid-2010s, much does not specifically address the issue of
MAUP. As examined by the research included in this systematic review, the concept of
spatial variability is designed to address MAUP. That is, crime varies by units nested
within other units and analyzing the phenomenon requires multi-level methodologies.
This largely follows the definition outlined at the beginning of this systematic review.
However, as evident by the plethora of methodologies and units examined from the
identified studies, that definition may be too narrow or ill-defined. Specifically, the
definition does not expand on what types of spatial and statistical relationships are of key
interest among the data being analyzed. For example, it is difficult to differentiate whether the studies that used tests of concentration (e.g., the nested Gini coefficient) across multiple spatial levels should be categorized as tests of concentration or spatial variability. The primary differentiating factor in this case is the nested analysis. Future work in this area will certainly benefit from refining the definition of spatial variability of crime.

There is also the issue of overlap between research examining crime concentration versus more spatially centric studies. In both cases, research is interested in understanding where crime occurs and at what levels. However, as previously discussed measures of crime concentration are statistical descriptions rather than true tests of spatial unevenness. There is room for overlap though, as evident from the studies included in this review. Some studies even use tests designed for examining crime concentration but across multiple levels (see O’Brien, 2019; O’Brien et al., 2021).

Based on the few studies selected as satisfactorily examining the spatial variability of crime, it is evident this branch of research is in the development phases. This systematic review is the first comprehensive bridge between these studies with a central focus on their methodological choices. The present study aims to serve as a guide to the choices being made for future research on this burgeoning topic. While many of the findings from the research on the spatial variability of crime mimic those on the concentration of crime, there are ample opportunities to parse the nuance of methodological choice. Additionally, research on this topic has the potential to invoke new theoretical progress that is hierarchically structured and methodically informed.
Central findings from this systematic review are that across the reviewed research a wide array of sample sizes, units, and methodologies are used. There is also a lack of research when compared to studies on the concentration of crime where a recent systematic review identified 44 studies from 1970-2015 (see Lee et al., 2017). Like research on crime concentration micro-places play an important role in our understanding of where crime occurs relative to other units. Of concern and as a recommendation for future research, replication is needed. Because many options exist on how to measure the spatial variability of crime and new ones being proposed, it appears replication is of little interest. Instead, pressure from pursuing the next innovative methodology may lure researchers away from replication. This is a harmful prospect as the concept of spatial variability is in development and without methodological guidance. Foundations are crucial for any topic of research for future research to build upon. Instead, as evident from this systematic review, that has not occurred yet or may not occur in the future.

References


CHAPTER 4

A NEW TEST OF THE LAW OF CRIME CONCENTRATION:
EXAMINING THE SPATIAL VARIABILITY OF ROBBERY WITHIN
AND BETWEEN EIGHT U.S. CITIES\textsuperscript{13}

Abstract

Objective

The law of crime concentration suggests the spatial distribution of crime at micro-places is consistent between cities. While previous research has assessed the law’s proposed distributional bandwidth of incidents, we conduct a new test which systematically examines the spatial variability of crime patterns within and between cities.

Data/Methods

This study observes robbery incidents reported to police departments across eight U.S. cities from 2015-2019. Incidents are geocoded to census blocks which are hierarchically nested within census tracts and cities. We calculate the spatial variability attributed to blocks and tracts using variance partitioning with multi-level negative binomial models and compare estimates between cities.

Results

Our findings support the law of crime concentration by observing minimal spatial variability between cities. Census blocks accounted for around 72-92% of the total spatial variability and census tracts just 8-28%. These variability estimates suggest city’s do not have a large effect on shaping the spatial distribution of crime patterns.

Conclusions

Despite the disparate physical and social characteristics of cities, the spatial distribution of crime is remarkably similar between most locations. Micro-places account for the largest amount of spatial variability. Future research should continue to explore the broader contexts in which these locations are found to have the most complete understanding of the relationship between crime and place.
Introduction

The history of crime and place research is generally characterized by a transition in focus from large to small spatial units of analysis (Weisburd et al., 2009). The earliest research examined spatial units such as countries and cities before shifting to neighborhoods and micro-places over long periods of time (Park & Burgess, 1925; Quetlet, 1831; Weisburd et al., 2012). Contemporary research on micro-places has garnered attention due to the disproportionate concentration of crime found at a small number of these hot spot locations (e.g., Sherman et al., 1989). Examples of micro-level units of analysis are street segments, street blocks, and other places found within neighborhoods (Eck & Weisburd, 1995). More recent studies have indicated micro-places provide a larger contribution to the overall spatial variability of crime patterns compared to neighborhoods (Steenbeek & Weisburd, 2016). These studies used a hierarchical framework which examined crime across at least two nested spatial units to understand how crime varies at different spatial scales within cities (see Hipp et al., 2020; Hipp & Williams, 2021; O’Brien, 2019; O’Brien & Winship, 2017; Quick, 2019; Schnell et al., 2017). These studies suggest researchers continue to scale-down from macro- or meso-units to understand more about where the “action” of crime occurs which is between micro-places in cities (see Steenbeek and Weisburd, 2016).

Weisburd (2015) proposed the law of crime concentration after observing remarkable consistency between cities regarding the distribution of crime at micro-places. Despite the wide range of differences in the social and physical characteristics of cities, the distribution of crime between micro-places is almost identical. Between 4-6% of micro-places in large cities and 2-4% in small cities account for 50% of crime
incidents. These findings suggest there is little influence of cities upon the distribution of crime at micro-places. In other words, there is not much difference between Charlotte, NC, and Cleveland, OH in where crimes occur or the spatial relationship between which locations have crime within these cities. Much research on micro-places is often bounded to observations of crime data from a single city (see Weisburd et al., 2012). There are only a few examples of research focused on micro-places which expands the spatial scope beyond a single city to consider differences between cities (see Hipp & Kim, 2017; Hipp & Williams, 2021). Most tests of the law of crime concentration only explore the distribution from a new, unstudied city (e.g., Gill et al., 2017) or examine measurements across varying temporal periods (e.g., Haberman et al., 2017). In addition, these studies do not provide a rigorous examination of the spatial distribution of crime incidents instead focusing on the statistical distribution or a bandwidth to summarize the distribution.

Our study provides a new test of the law of crime concentration which reexamines the proposal that the spatial distribution of crime is consistent between cities. Our analytic framework builds upon previous hierarchical studies to examine the spatial variability of crime within and between cities. We present a systematic sampling strategy to identify eight cities for the comparison of robbery patterns. Together, we use the hierarchical nesting of micro-places within neighborhoods and spatial weights to offer a more robust spatial consideration of the law of crime concentration. Previous tests of the law of crime concentration imply the role of cities in shaping the spatial distribution is minimal but these analyses do not provide a direct test of this proposition. This study directly addresses the question: do cities provide a unique contribution to understanding
the spatial variability of crime? If there is some spatial variability accounted for by cities, this would suggest continued inquiry into the explanations for this variability. What about cities helps shape their unique spatial distribution of crime patterns? This would also lead to further reconsideration of place-based crime prevention strategies which are more tailored to the characteristics of specific cities instead of more generalized approaches. The next section provides a more detailed literature review before we discuss the research methodology for this study.

Examining Crime Variability Across Multiple Spatial Units

Crime and place research has increasingly investigated spatial variability across multiple place-based units of analysis within cities (Deryol & Payne, 2021; Duru & Kim, 2021; Lee et al., 2017; Umar et al., 2021). This is important because the modifiable aerial unit problem (MAUP) is a key consideration for any spatial analysis. The MAUP forces researchers to consider the benefits and costs to prioritizing any single spatial unit of analysis over the wide range of alternatives (Openshaw, 1984). Examining multiple spatial levels is important because meso- and macro-units can provide important context to localized processes (Baumer et al., 2012; Hipp & Williams, 2021; Jones & Pridemore, 2019; Lyons et al., 2013). This research has consistently found that most of the spatial variability of crime occurs at the micro-level. However, the influence that meso- and macro-level units have on crime variability is still noteworthy. By studying neighborhoods researchers could miss out on micro-variability within these units or by studying micro-places researchers ignore the higher-order clustering of patterns within neighborhoods. Andresen (2011) explored local crime clusters across census tracts and dissemination areas which are equivalent to census blocks in Vancouver, Canada. A local
analysis of spatial autocorrelation conducted on aggregated counts of crime incidents at both units revealed similar measures of variance. However, the observed differences between the levels are an important feature of the unit choice. If only a single spatial unit had been analyzed, the conclusions drawn would have disregarded hidden spatial heterogeneity at different spatial levels.

Two recent studies helped create a template for hierarchical frameworks to analyze spatial variability of crime between different units of analysis. Steenbeek and Weisburd (2016) estimated linear mixed models on crime incident data nested across street segments (i.e., micro), neighborhoods (i.e., meso), and districts (i.e., macro) in The Hague, Netherlands. These analyses permitted the calculation of easily interpretable variance partition components (VPC) which assign a unique contribution of the total spatial variability to each spatial unit of analysis. A temporal component was also included as a fixed effect nested within micro-places providing the first hierarchical level. To calculate the variance attributed to each spatial unit, the variance depended on time, as it was allowed to vary randomly per spatial level. Supporting prior research, the authors found the most total variability occurring at the micro-level with approximately 58-69% attributed to street segments depending on the year. The remaining 31-42% of variability was attributed across both meso- and macro- units of analysis. This study was replicated using Chicago robbery data whereas Schnell et al. (2017) similarly observed a range of 56-65% attributed to street segments. Notable, is the large share of variability attributed to the neighborhood was found at macro- instead of meso- units (districts and community areas, respectively).
Linear mixed models are not the only method of analysis used in recent studies. O’Brien (2019) relied on Gini coefficients by calculating a global and nested distributional coefficient. For example, the nested coefficients were calculated per unit and then used to evaluate concentrations at the lower unit. When fewer events occurred relative to the number of units, a generalized Gini coefficient was calculated (see Bernasco & Steenbeek, 2017). Using these methods, O’Brien (2019) observed concentrations of crime were highest at street segments and lowest at census tracts. In a different study, logistic regression models were used by Hipp et al. (2020) to compare the relative robbery risk across three spatial scales and a temporal scale. Results from their full model indicated that, like prior research, street segments (micro-level) contribute the greatest measure of unique variance when compared to other spatial levels. However, when the variance estimates for the meso- and macro-level measures are combined, the proportion of explained variance is comparable to the micro-level measures which highlights the importance of larger spatial scales. Another recent study incorporated a Bayesian modeling technique that also observed the largest variance attributed to the smallest unit of analysis included within the multilevel models (Quick, 2019). In his study, cross-classified Bayesian multilevel models were calculated for lower and higher-level units that were non-nesting at the higher-level. When combined, the three higher-level units analyzed explained 15% of the total variation of violent crime with neighborhoods accounting for the majority of the variance.

The law of crime concentration is constructed around Weisburd’s (2015) observations on the distribution of crime across eight cities. The law was influenced by Sherman and colleagues (1989) seminal findings on crime spots in Minneapolis and the
Pareto Principle or the 80/20 rule from outside of criminology (Pareto, 1909). These cities were located across most regions of the United States, and one was in Israel with populations from around 70,000 (i.e., Redlands, CA) to over 8,000,000 residents (i.e., New York, NY). In turn, these cities had disparate social and physical characteristics. For example, the poverty rate in Cincinnati, OH was more than two times higher than in Seattle, WA and Tel-Aviv, Israel has 4.2% Black residents while Brooklyn Park, MN has 24.0%. The physical characteristics differed regarding the square milage of the cities and length of street segments. In addition, the number of crime incidents and crime rates varied drastically between cities. Despite these differences, across all cities 2-6% of street segments accounted for 50% of crime incidents. The bandwidths are even closer when separating between small (i.e., 2-4%) and large (i.e., 4-6) cities. While research has supported the law of crime concentration (see Eck et al., 2017; Gill et al., 2017; Haberman et al., 2017), other researchers have advocated for more standardized measures of crime concentration such as Gini coefficients or Lorenz curves (see Bernasco & Steenbeek, 2017). These measurements of spatial concentration only tell a small part of the story of where crime occurs within cities. These are measurements of statistical distributions and do not account of the spatial relationship or the actual location where these incidents are found within cities.

Previous scholarship has argued for the importance of understanding local processes while recognizing the broader geographic context they are found within. One of the lasting impacts of the Chicago School was the focus on cities as a critical spatial unit of analysis and seeking to understand the organization of places within cities (Park & Burgess, 1925). Cities often provide the overarching boundary for most research on
neighborhoods and micro-places. However, city-wide characteristics are often ignored, or studies are just conducted in a few cities in the United States (e.g., Chicago). These characteristics could matter for several reasons. The role of city-specific characteristics is potentially influential because these units of analysis can inherently shape everything found within them (see Kim & Hipp, 2018). Specifically, political differences and histories between cities have influenced drastically different policies, police practices, urban layouts, and demographic distributions that could consequently influence crime patterns in different ways (Hipp & Williams, 2021). Through this downward influence, city-wide characteristics could affect processes at smaller geographic levels, providing for unique differences between cities regarding the spatial distribution of crime. This questions the generalizability of results which might not expand beyond the boundary of the city examined.

Cities are salient ecological spaces that vary widely and assuming crime is spatially distributed with comparable patterns between them could be problematic. It is possible that differences do exist and estimates of crime variability per units of analysis are not similar for all cities. To the authors’ knowledge, we present the first study to systematically select cities and standardized crime variability measures for comparisons at multiple levels within cities. We provide further investigation of the finding that micro-places account for the most spatial variability and continue to unpack the role of cities in the accounting for differences in the spatial distribution of crime patterns.
Data And Methods

Present Study

This study uses techniques for partitioning multi-level variance to examine the spatial variability of robbery incidents at multiple spatial levels within and between eight U.S. cities. This analytic framework expands upon recent studies which have conducted variance partitioning for within city analyses (see Steenbeek & Weisburd, 2016). Our research design is informed by the methodology of systematic reviews and meta-analyses which provide a transparent search process and comparison of results between studies (e.g., Braga & Weisburd, 2020). Robbery incidents are analyzed at both micro-places and neighborhoods within cities. The standardization of results allows for the comparison between each city of estimates. Therefore, the range between estimates from each location can be attributed to between city variation (see Weisburd, 2015). Crime maps and descriptive statistics are used to supplement these findings to provide further understanding of the unique contribution of cities to the spatial distribution of crime incidents. Multi-level negative binomial models are estimated to determine the variability attributed to the micro- and meso- spatial units within each city. The overarching goal of this study is providing a test of the proposition of the law of crime concentration that the spatial distribution of incidents does not vary between cities.

Units of Analysis

Three spatial units of analysis are observed: census blocks (i.e., micro), census tracts (i.e., meso), and city boundaries (i.e., macro). The use of census geographic boundaries is commonplace among crime and place research (see Weisburd et al., 2012 for discussion). These units of analysis were selected because they are already by-design
nested. Census blocks are generally representative of street blocks which grounds these units within the street grid which is common for representations of micro-places (Eck & Weisburd, 1995; Grannis, 1998). These units are designed to be nested within census tracts which are often used as proxies for neighborhoods. Both units are also standardized across distinct cities in the U.S. which helps facilitate between city comparisons (see Peterson & Krivo, 2010). These micro- and meso- units have been extensively explored throughout the last fifty years (Lee et al., 2017; Walker & Drawve, 2018). A base map for each spatial level per city was created by obtaining the appropriate boundary data from the tidyCensus and tigris packages in R provided by the U.S. Census Bureau.

This study uses a systematic approach to identify a sample of cities to analyze. This provides a contrast to Weisburd’s (2015) analysis which created a convenience sample for his proposal of the law of crime concentration. The increased availability of public data provides various options of cities which could be considered for inclusion in our analysis. The construction of our sample was guided by several criteria. First, the sample was restricted to U.S. cities with populations greater than 100,000 residents (U.S. Census Bureau, 2019). While Weisburd (2015) does examine two cities with populations

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14 Census blocks are used instead of street segments which are one of the most examined measures of micro-places today for two main reasons. First, the creation of accurate street segment maps for multiple cities is not feasible due to time constraints. The process of accessing streets shapefiles for cities is not difficult but the transformation of these streets’ files into accurate street segment files is challenging. While the process is straightforward, the manner of cleaning a street segment shapefile for any abnormalities resulting from the over-estimation of the number of street segments is labor intensive (see Schnell et al., 2017, footnote 6). Second, there are advantages to the use of census blocks because they permit more accuracy for the geocoding process which was a key consideration to minimize any errors during this process across these different cities. These polygon features enhance the accuracy to which crimes can be geocoded because all crimes captured within the polygon will be included rather than attributing crimes to the nearest street segment when there is ambiguity. There is also the issue of crimes geocoded to intersections or major roadways. Often, these crimes cannot be directly attributed to a street segment and must manually be placed by the researcher or removed from analysis. Using census blocks minimizes this concern since polygon features are much larger than the average street segment, thus, it is easier capturing all crimes falling within the polygon.
under 100,000, we decided to restrict our eligibility. Larger cities have more crime incidents which minimizes concerns about statistical power and provides more potential crime incidents to study which helps the observation of variance. Second, only cities that provided all crime incidents reported to the police publicly through an online portal were considered (see footnote). 15 Several pre-existing sources were referenced to determine which cities had public data and a hand-search of each of the remaining cities was conducted. 16

Third, the available crime incident report data had to span five years. The use of multiple years helps minimizes the influence of any potential outlier years. We selected from 2015-2019 which covers the last five full years before the COVID-19 pandemic (i.e., March 2020). Fourth, the crime incident data had to include XY coordinates to minimize geocoding concerns across these disparate jurisdictions. Using these selection criteria, 15 eligible locations were identified, and eight cities were randomly selected. The inclusion of each additional city is labor intensive, and we decided mirroring the number included by Weisburd (2015) was appropriate for this test. The selected cities include Atlanta, GA, Austin, TX, Cincinnati, OH, Denver, CO, Gainesville, FL, Los Angeles, CA, Orlando, FL, and Philadelphia, PA. The crime data were then downloaded via each city’s open data portal. Table 4.1 shows the characteristics of each city regarding


16 Using keywords, “open portal”, and “crime data”, sources identified were https://www.policedatainitiative.org and https://www.data.gov. Other research on this topic provided a helpful tool for the recollection of which cities had public data. For example, Schnell et al. (2017) used data from Chicago’s data portal. Larger cities are commonly more adept at making their crime data open and accessible to the public. Searching all cities over 100,000 in population for appropriate data proved too time consuming to do strictly by hand.
population estimates, spatial units, and the size of each city. The sample represents a geographically diverse collection of cities with much variation in population and the overall size of the city. To illustrate the nesting of each spatial unit, Figure 4.1 contains maps of Austin and Denver.

<table>
<thead>
<tr>
<th>City</th>
<th>(a) 2019 Population estimates</th>
<th>(b) N spatial units</th>
<th>(c) City Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta, GA</td>
<td>506,811</td>
<td>6,735</td>
<td>139</td>
</tr>
<tr>
<td>Austin, TX</td>
<td>978,908</td>
<td>10,732</td>
<td>213</td>
</tr>
<tr>
<td>Cincinnati, OH</td>
<td>303,940</td>
<td>4,606</td>
<td>114</td>
</tr>
<tr>
<td>Denver, CO</td>
<td>727,211</td>
<td>11,011</td>
<td>144</td>
</tr>
<tr>
<td>Gainesville, FL</td>
<td>133,997</td>
<td>2,494</td>
<td>41</td>
</tr>
<tr>
<td>Los Angeles, CA</td>
<td>3,979,576</td>
<td>30,565</td>
<td>1,001</td>
</tr>
<tr>
<td>Orlando, FL</td>
<td>287,442</td>
<td>4,768</td>
<td>75</td>
</tr>
<tr>
<td>Philadelphia, PA</td>
<td>1,584,064</td>
<td>18,872</td>
<td>384</td>
</tr>
</tbody>
</table>

**Crime Incidents**

Due to the unique reporting procedures of each city’s police departments, there were substantial differences when comparing crime data. For example, incident reports of domestic violence, sexual battery, and sexual assault among other crimes were excluded from the public data in Orlando. Only UCR Part I crimes were accessible from Atlanta. Most of the cities followed NIBRS-based reporting procedures while others followed UCR procedures. Nevertheless, across all cities the reporting of robbery incidents was consistent. Due to this uniformity, our study focuses exclusively on the spatial distribution of robbery incidents.
Figure 4.1 Spatial units used in the study for Austin (left) and Denver (right): blocks (thin solid lines) nested in tracts (dashed borders) nested in the city (solid thick border)
Robbery incidents have high-reporting rates relative to other crimes and these violence crimes occur often enough to provide enough incidents for observation (Andresen & Linning, 2012). In addition, there is a large collection of studies on crime and place which examine robbery and provide helpful reference points for this research (Bernasco & Block, 2011; Block & Block, 1995; Braga et al., 2011; Hipp et al., 2020). Table 4.2 provides an overview of the total robbery counts over the observation period and geocoding results for each city. Each city meets standard acceptable thresholds for geocoding rates (see Andresen et al., 2020). To create count variables of robbery incidents for each city, robbery incidents were spatially joined to census blocks. The number of robbery incidents per census tract were aggregated from the number of census blocks within those units.

<p>| Table 4.2 Robbery characteristics by city, 2015-2019 |
|---------------------------------|---------------------------------|-----------------|</p>
<table>
<thead>
<tr>
<th>(a) Reported Robbery Incidents</th>
<th>(b) Total Robbery Incidents After Geocoding</th>
<th>(c) Geocoding Rates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta</td>
<td>8,440</td>
<td>8,433</td>
</tr>
<tr>
<td>Austin</td>
<td>2,587</td>
<td>2,587</td>
</tr>
<tr>
<td>Cincinnati</td>
<td>3,582</td>
<td>3,539</td>
</tr>
<tr>
<td>Denver</td>
<td>7,170</td>
<td>7,141</td>
</tr>
<tr>
<td>Gainesville</td>
<td>891</td>
<td>884</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>50,735</td>
<td>50,446</td>
</tr>
<tr>
<td>Orlando</td>
<td>2,897</td>
<td>2,795</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>34,128</td>
<td>33,887</td>
</tr>
</tbody>
</table>

**Analytic Strategy**

This study involves two stages of analysis. The first stage involved calculating descriptive summary statistics of crime concentration at each spatial level per city using the threshold of 50% as discussed by Weisburd’s (2015) law of crime concentration.
Additionally, Lorenz curves and Gini coefficients are used to provide more comprehensive representations (Gini, 1912; Lorenz, 1905). The use of these descriptive measures is commonplace when examining spatial concentration of crime (Bernasco & Steenbeek, 2017; Hipp & Kim, 2017; Mohler et al., 2017). However, these measures only provide helpful contrasts between spatial units and do not provide any indication of the direct, nested spatial variability between units. For a more illustrative presentation of crime concentration, choropleth maps are used to show the spatial concentration of robbery.

In the second stage of analysis, we conducted variance partitioning to determine the unique contribution of the micro- and meso- units of analysis to the spatial variability of robbery patterns. Afterwards, we compare these results between cities. We initially considered the use of a linear mixed model to calculate city-level estimates of spatial variability. To build upon these hierarchical analyses (see Steenbeek & Weisburd, 2016), the original plan for this research was to generally replicate their models using a fixed effect to estimate longitudinal time trends at level-1 of the four-level model. The remaining levels of the model, in order, were the census blocks (level-2), census tracts (level-3), and cities (level-4). However, before any analyses were conducted the low number of level 4 groups (i.e., eight cities) were anticipated to present statistical challenges leading to low confidence in any findings and likely convergence issues (see Hox, 1998; Nezlek & Gelman, 2006; Richter, 2006). As anticipated during our preliminary analyses, the original model used in this study was not appropriate. Different iterations of the model would not fully converge and using multiple optimizers from the
R package *Lmer* were tested to no avail.\(^{17}\) Other methods such as using a generalized-linear model also had convergence issues. To continue addressing the potential differences between cities, it was decided to separate each model per city and aggregate all crime incidents across time to improve crime counts per unit.

The calculation of variance partition coefficients for multi-level models with count data is guided by Leckie et al.’s (2019) discussion (also see Austin et al., 2017; Goldstein et al., 2002). Calculating the variance partitioned coefficients (VPC) allows for the proportion of the response variance (i.e., robbery incidents), to be estimated. Thus, the VPC identifies the importance clusters have on the response. In our case, the importance of census blocks, and tracts beyond the modelled outcomes. Calculating the VPC for multilevel count models is less straightforward. However, Leckie et al. (2019) have outlined such a method building upon Austin et al. (2017) who used simulation testing for VPCs of Poisson models. Leckie et al. (2019) have extended the equations to also fit negative binomial models as many count models, particularly, multilevel models are characterized by overdispersion. This study utilized a technique for our primary analysis that directly replicated the VPC mathematics from Leckie et al. (2019). These formulae were used because they are relatively straightforward and provided easy to understand estimates that can be used to compare between cities. The entire process of data collection, cleaning, and modeling was the same for each city in this study.

To begin, for each city, a two-level Poisson model was fitted with the total robbery incidents from 2015-2019 as the response variable. Counts of robbery were calculated at each level of the model with census blocks as the level-1 explanatory

\(^{17}\) These included ‘nlminb’, ‘Nelder_Mead’, ‘bobyqa’, and ‘L-BFGS-B’.
variable and census tracts as the level-2 variable. Let $y_{ij}$ denote the robbery incident count for block $i$ in tract $j$. To account for potential overdispersion, two-level negative binomial models were also fitted and compared to the Poisson model. The negative binomial model can be written as:

$$
\begin{align*}
    y_{ij} \mid \mu_{ij} &\sim \text{Poisson}(\mu_{ij}) \\
    \ln(\mu_{ij}) &= \beta_0 + \mu_j + e_{ij} \\
    \mu_j &\sim N(0, \sigma_u^2) \\
    \exp(e_{ij}) &\sim \text{Gamma}(\frac{1}{\alpha}, \alpha)
\end{align*}
$$

where $e_{ij}$ denotes the overdispersion random effect. The overdispersion random effect is exponentiated and assumed to have a gamma distribution with scale parameters for $\alpha$.

The larger the value for $\alpha$, the greater overdispersion that is present compared to the Poisson model. Preference for the Poisson model is given when $\alpha = 0$. To simplify the included mathematical notation only the equation for the VPC is provided. For the conditional and marginal statistical equations refer to Leckie et al. (2019). The following VPC equation allows for level-specific components and captures within- and between-cluster variance in $y_{ij}$. The VPC equation used can be written as:

$$
VPC_{ij} = \frac{(\mu_{ij}^M)^2\{\exp(\sigma_u^2) - 1\}}{(\mu_{ij}^M)^2\{\exp(\sigma_u^2) - 1\} + \mu_{ij}^M + (\mu_{ij}^M)^2\exp(\sigma_u^2)\alpha}
$$

where the numerator and likewise equation in the denominator is a measure of the level-2 variance. The other share of the denominator is a measure of the level-1 variance. To account for overdispersion, the VPC is now a decreasing function of $\alpha$ such that as overdispersion increases there is more unmodelled variation at level-1, thus the VPC decreases. While $\alpha$ alone does not indicate true significance for preference over the
Poisson model, the VPC estimates in conjunction allow for a better comparison. Particularly, when aided by prior research and theory.

We first examine constant-only models. As a comparison model, we included an independent variable which provides a spatial weight for the level of robbery in surrounding areas of both census blocks and tracts. Spatial weights using a queen-contiguity matrix were created for census blocks and tracts using the counts of neighbors’ robberies per unit. The motivation for creating the weights in this manner was that for spatial units that have more neighbors, if those neighbors have high robbery counts, there is likely a spatial relationship due to proximity influencing localized crime rates. While hierarchical studies build upon other descriptive analyses from crime and place research, they are not explicitly spatial. The designation of hierarchical nesting implies a spatial relationship of level-1 units within level-2 units since they are treated as connected. This approach does not account for the influence of the immediate surrounding areas to both census blocks and tracts which is much more aligned with the measurement of the concept of spatial interdependence (Bernasco & Elfers, 2010). Combined with the hierarchical nesting a spatial weight variable provides a more realized representation of spatial relationships.

Due to the focus on examining the descriptive spatial variability of robbery across different levels of geography, no other covariates were not added to the models. The interest of this study is not to explain the variability of robbery by time-constant or time-varying predictors but providing a baseline representation of variability (see Steenbeek & Weisburd, 2016). These descriptive representations are helpful to inform research about the levels of aggregation to explore for the explanation of patterns. These are cross-
sectional models which do not examine the impact of time. Again, this decision was to simplify model estimates and provide adequate variance at level-1 for larger cities such as Los Angeles which has over 30,000 blocks. All statistical analyses were conducted using the R statistical programming language. Packages such as \textit{Lme4} and \textit{glmmTMB} were used to estimate the multi-level models. As no package exists to succinctly calculate the VPC, the equation was programmed and calculated for each city (see Leckie et al., 2019).

\textbf{Results}

\textbf{Descriptive Statistics}

Table 4.3 presents the summary descriptive statistics for the distribution of robbery across cities. Between cities there is a wide range of the total number of census blocks which experienced a robbery during the observation period (see column a). Austin had only 8.6\% of the blocks with a robbery while Philadelphia had 52.1\%. Most census tracts experienced a robbery with 6 of 8 cities reporting over 90\% of the locations had a robbery. There was noteworthy concentration of robbery incidents at a small number of blocks with 7 of 8 cities having 5\% or fewer of locations account for 50\% of incidents (see column b). The distribution is less concentrated when considering the raw number of locations which did experience a robbery incident (see column c). These estimates in column (c) present a more conservative calculation of concentration (see Levin et al. 2017). The block figures are much more comparable to each other and census tracts with this adjustment to the denominator for calculations. These statistics provide support to the law of crime concentration by noting a relatively consistent concentration of robbery across all cities. Conversely, these findings indicate important differences in the number
of locations which experience crime events. Most micro-places in cities do not experience crime incidents (i.e., datasets are zero-inflated). The number which do, appear influenced by the total number of crimes and the physical layout of the location which determines the total number of micro-units. While there is much consistency between cities the location of Philadelphia appears an outlier with more locations having robberies although the concentration of incidents appears comparable when accounting for the number of locations with incidents.

Next, we explore the spatial distribution of robbery across the two units of analysis within cities between 2015-2019. Figure 4.2 compares the distribution of robbery clusters between Atlanta and Gainesville using choropleth maps. Between both cities census tracts, robbery is concentrated towards the center of each city rather than the municipal edges. Atlanta has areas of higher concentration in southernmost tracts compared to northernmost tracts. For both cities the areas of high robbery concentration by census block appear dispersed and less uniform. Across both cities, clusters of high robbery blocks are present in multiple areas. Due to the large number of the micro-units of analysis for each city, viewing concentration at the block-level is difficult. To further illustrate the concentration of robbery at the census block, Figure 4.3 displays a more precise view of these spatial units within southeast Atlanta. This figure illustrates that robbery is heavily concentrated in this section of the city. For this area, blocks with high levels of robbery are directly adjacent to blocks with little to no robbery. This map further

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18 The Fisher-Jenks method was utilized for the maps presented in Figure 2. This method is an iterative optimization often used to display “natural breaks” of geographic data (Fisher, 1958).
confirms that areas can be relatively safe and robbery-free while being located next to more robbery-prone areas (see Weisburd et al. 2012).

Table 4.3 Percent of spatial units accounting for 50% of robbery for all cities, 2015-2019

<table>
<thead>
<tr>
<th></th>
<th>Blocks</th>
<th>Tracts</th>
<th>Blocks</th>
<th>Tracts</th>
<th>Blocks</th>
<th>Tracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta</td>
<td>36.1</td>
<td>93.5</td>
<td>5.5</td>
<td>23.0</td>
<td>15.3</td>
<td>24.6</td>
</tr>
<tr>
<td>Austin</td>
<td>8.6</td>
<td>75.1</td>
<td>1.2</td>
<td>9.9</td>
<td>14.4</td>
<td>13.1</td>
</tr>
<tr>
<td>Cincinnati</td>
<td>25.0</td>
<td>93.9</td>
<td>4.2</td>
<td>18.4</td>
<td>16.9</td>
<td>19.6</td>
</tr>
<tr>
<td>Denver</td>
<td>21.2</td>
<td>100.0</td>
<td>3.1</td>
<td>19.4</td>
<td>14.5</td>
<td>19.4</td>
</tr>
<tr>
<td>Gainesville</td>
<td>12.9</td>
<td>75.6</td>
<td>2.7</td>
<td>14.6</td>
<td>20.9</td>
<td>19.4</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>30.1</td>
<td>98.7</td>
<td>3.3</td>
<td>15.1</td>
<td>10.9</td>
<td>15.3</td>
</tr>
<tr>
<td>Orlando</td>
<td>15.8</td>
<td>90.7</td>
<td>2.2</td>
<td>10.7</td>
<td>14.2</td>
<td>11.8</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>52.1</td>
<td>99.5</td>
<td>9.7</td>
<td>24.2</td>
<td>18.6</td>
<td>24.3</td>
</tr>
</tbody>
</table>

The Lorenz curves in Figure 4.4 illustrate the robbery concentration per unit in each of the eight cities. For all cities, robbery was most concentrated at the block-level. To aid interpretation of robbery concentration, Table 4.4 contains the Gini coefficients by unit for each city. The generalized Gini coefficients are also shown in columns (c) and (d) of Table 4.4 (see Bernasco & Steenbeek, 2017). Generalized Gini coefficients are a method for capturing a more accurate level of crime concentration as in many cases places outnumber observed crime. In cases this imbalance occurs, biased estimates are can impact interpretations of the distribution of incidents. Presently, the Gini coefficients
using both methods did not differ for tract-level estimates because almost all locations experienced robberies. The coefficients using the standard Gini range from 0.714-0.955. As expected, small differences do exist among the block-level estimates because for 5 of 8 cities the number of blocks analyzed exceeds the number of robbery incidents observed. In each case, the Gini coefficient decreased using the generalized method (ranging from 0.714-0.877). The differences range from 0.07-0.237 with Gainesville having the largest reduction. This is an expected result as Gainesville had the fewest incidents of robbery (884) compared to blocks (2,494), an almost three-fold increase of units compared to crime. No difference was observed for Atlanta, Los Angeles, or Philadelphia as each city had more robbery incidents than blocks.

Table 4.4 Gini coefficients by unit of robbery, 2015-2019

<table>
<thead>
<tr>
<th></th>
<th>Gini Coefficients</th>
<th>Generalized Gini Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(a) Block-level</td>
<td>(b) Tract-level</td>
</tr>
<tr>
<td></td>
<td>coefficients</td>
<td>coefficients</td>
</tr>
<tr>
<td>Atlanta</td>
<td>0.819</td>
<td>0.443</td>
</tr>
<tr>
<td>Austin</td>
<td>0.955</td>
<td>0.695</td>
</tr>
<tr>
<td>Cincinnati</td>
<td>0.866</td>
<td>0.512</td>
</tr>
<tr>
<td>Denver</td>
<td>0.890</td>
<td>0.470</td>
</tr>
<tr>
<td>Gainesville</td>
<td>0.922</td>
<td>0.617</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>0.877</td>
<td>0.542</td>
</tr>
<tr>
<td>Orlando</td>
<td>0.923</td>
<td>0.634</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>0.714</td>
<td>0.425</td>
</tr>
</tbody>
</table>
Figure 4.2 Choropleth maps of robbery counts per units (blocks on left; tracts on right) for Atlanta and Gainesville.
Figure 4.3 Choropleth map of robbery counts per block for SE Atlanta
Figure 4.4 Lorenz curves for each city of robbery per unit from 2015-2019.
The Gini coefficients for tracts among all cities range from 0.425-0.695. Like Schnell et al. (2017) and Steenbeek and Weisburd (2016) the coefficients for micro-units did not fall below 0.7. One noteworthy difference, the coefficients for 4 of the 8 cities are substantially higher than those observed in prior research for comparable units. For example, the tract-level coefficient for Austin (0.695) almost rises to levels of concentration observed at the micro-place. Other cities though have estimates in-line with prior research (< 0.5) for meso-level units. Nonetheless, it is notable there is a degree of difference for robbery concentration between all cities across these units.

**Variance Estimates**

We first estimated multi-level Poisson models with robbery aggregated to the census blocks nested within census tracts for each city (see Leckie et al., 2019). Due to the anticipated overdispersion of robbery counts we estimated multi-level negative binomial models to account for this distributional feature of the data. The $\alpha$ values for the negative binomial models were $\alpha > 0$, which paired with other model fit tests indicated the presence of overdispersion in the Poisson models. Table 4.5 reports the negative binomial estimates for each city across 2015-2019. Of particular interest are the Level-2 and Level-1 VPC marginal estimates.

To facilitate interpretation, the VPC for each city for all three models were transformed into percent estimates. These estimates are presented in Table 4.6 and represent the proportion of robbery attributed to each unit compared to the total variance of robbery. The Model 1 estimates differ greatly compared to the other two models due to this overdispersion and attributing greater variability to the census tracts. Using the estimates from Model 2 and Model 3, across all cities, a clear pattern of robbery
variability emerges. Like levels of concentration, robbery incidents vary the most at the
census block-level. Across all cities, the variability of robbery ranges from 71.8% -92.2%
using Model 2. A smaller proportion of robbery varies at the tract-level, with a range of
7.8% -28.2% for Model 2. These ranges for both units across all cities are comparable to
the estimates from Model 3 which included spatial weights. In addition, separate negative
binomial models for each city were calculated by year which are available upon request.
These estimates attribute more variability to blocks with approximately 83% -99% of
total spatial variability and tracts 2% -16% of variability. No single year per city
presented an outlier instead estimates for each city were relatively stable.

The VPCs expand upon the results of our descriptive analyses in demonstrating
the importance of micro-units (Weisburd, 2015). The results also highlight the continued
importance of higher-order spatial units such as the census tract when estimating
proportions of robbery variability. Like other research that has explored spatial
variability, our work further supports findings of nested crime variability with micro-
units accounting for most of the total variability, with neighborhoods accounting for a
small but essential share of the variability (Quick, 2019; Schnell et al., 2017; Steenbeek
& Weisburd, 2016). Our results are the first to systematically examine between-city
differences of the spatial variability of robbery. Differences of VPC estimates between
the cities exist but are quite modest. This is despite the vast differences between the cities
such as geographic size, number of robbery incidents, and the number of spatial units.
Table 4.5 Negative binominal estimates for variance components fitted to the 2015-2019 robbery data for all cities

<table>
<thead>
<tr>
<th>Parameter Estimates</th>
<th>Atlanta</th>
<th>Austin</th>
<th>Cincinnati</th>
<th>Denver</th>
<th>Gainesville</th>
<th>Los Angeles</th>
<th>Orlando</th>
<th>Philadelphia</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$ - Intercept</td>
<td>-0.096</td>
<td>-2.459</td>
<td>-0.701</td>
<td>-0.852</td>
<td>-1.677</td>
<td>0.036</td>
<td>-1.122</td>
<td>0.206</td>
</tr>
<tr>
<td>$\sigma_u^2$ - Tract variance</td>
<td>0.787</td>
<td>2.346</td>
<td>1.211</td>
<td>0.847</td>
<td>1.121</td>
<td>2.047</td>
<td>1.175</td>
<td>0.782</td>
</tr>
<tr>
<td>$\alpha$ - Overdispersion</td>
<td>2.915</td>
<td>7.199</td>
<td>2.974</td>
<td>4.172</td>
<td>6.971</td>
<td>3.992</td>
<td>6.258</td>
<td>1.127</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Marginal Estimates</th>
<th>Marginal Expectation</th>
<th>Marginal Variance</th>
<th>Level-2 Component</th>
<th>Level-1 Component</th>
<th>Level-2 VPC</th>
<th>Level-1 VPC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.346</td>
<td>0.276</td>
<td>0.909</td>
<td>0.651</td>
<td>0.328</td>
<td>2.047</td>
</tr>
<tr>
<td></td>
<td>2.169</td>
<td>0.721</td>
<td>1.950</td>
<td>0.566</td>
<td>0.222</td>
<td>12.163</td>
</tr>
<tr>
<td>Deviance</td>
<td>17529</td>
<td>8485</td>
<td>8564</td>
<td>18121</td>
<td>2785</td>
<td>75473</td>
</tr>
</tbody>
</table>
Table 4.6 Variance proportions for each city across each model

<table>
<thead>
<tr>
<th></th>
<th>Model 1: Poisson</th>
<th>Model 2: Negative Binomial</th>
<th>Model 3: Negative Binomial w/ spatial Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Level-1 VPC</td>
<td>Level-2 VPC</td>
<td>Level-1 VPC</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Level-2 VPC</td>
</tr>
<tr>
<td>Atlanta</td>
<td>11.0%</td>
<td>89.0%</td>
<td>85.7%</td>
</tr>
<tr>
<td>Austin</td>
<td>19.0%</td>
<td>81.0%</td>
<td>89.4%</td>
</tr>
<tr>
<td>Cincinnati</td>
<td>27.2%</td>
<td>72.8%</td>
<td>82.5%</td>
</tr>
<tr>
<td>Denver</td>
<td>48.2%</td>
<td>51.8%</td>
<td>89.4%</td>
</tr>
<tr>
<td>Gainesville</td>
<td>41.5%</td>
<td>58.5%</td>
<td>92.2%</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>11.0%</td>
<td>89.0%</td>
<td>84.7%</td>
</tr>
<tr>
<td>Orlando</td>
<td>32.7%</td>
<td>67.3%</td>
<td>90.8%</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>30.5%</td>
<td>69.5%</td>
<td>71.8%</td>
</tr>
</tbody>
</table>

For all cities, the Model 3 estimates were marginally preferred to the Model 2 estimates based on goodness of fit statistics. Additionally, the variance estimates for each spatial unit within each city were almost identical between the two methods. However, concerning marginal estimates and $\beta_0$ values made for complicated interpretation. Because of the interpretation issues, the marginal difference between Model 2 and 3 VPCs, and preference for parsimony Model 2 was identified as the superior fit for this study.

**Conclusion**

This study conducts a new test of the law of crime concentration and our findings provide continued support for the key components of this law. Our findings reaffirm the importance of micro-places for examining the spatial distribution of crime within cities. Robbery incidents were concentrated at a small number of micro-places and the total spatial variability accounted for by micro-places was substantial. Between 71.8% and 92.2% of the total spatial variability of robbery is accounted for by census blocks.
between the eight U.S. cities we examined. The remaining 7.8%-28.2% of the total spatial variability is attributed to the census tracts. Our study provided unique insight on the role of cities in understanding the spatial variability of crime patterns. In general, cities played a modest role with the range of estimates at both micro-places and neighborhoods varying around only 20%. Combined, these results provide the foundation of a new distributional bandwidth which summarizes this variability. Across these eight cities, an average of 85.8% is attributed to micro-places and 14.2% to neighborhoods with the standard deviation capturing the potential city-level effect around 6.5%. These findings reinforced the importance of understanding local processes as functions of larger geographic spaces (Braga et al., 2011; Groff et al., 2010; Malleson et al., 2019; Sherman & Weisburd, 1995). These findings support the key observation from the law of crime concentration that despite varying social and physical characteristics of cities the spatial distribution of crime incidents at micro-places is remarkably consistent. More so, our systematic approach to examine city-to-city differences has found that despite the discernable differences between two cities such as Los Angeles and Orlando, estimates of the spatial variability of robbery between cities are similar.

There are implications of this research for place-based theories, methodology, and crime prevention. While our estimates of the city-level effect on the spatial variability of robbery were small they still warrant further investigation. In addition, 7 of 8 cities estimates were relatively comparable but Philadelphia’s estimates were more divergent. Collectively, there is little theoretical understanding of the forces which could influence differences in the spatial distribution of crime between cities. How is the opportunity structure for crime both similar and different across these spaces (see Weisburd et al.,
2012)? The conceptualization of these potential differences is difficult to grasp. Based on our assessment key considerations would include the number of locations which experience crime, the degree of distributional concentration of these incidents, and extent of variability across key spatial units of analysis. These differences could be the result of more simple features such as a physical characteristics like a city’s expansion was limited by the proximity to a body of water or mountain range. On the other hand, these differences could be the result of more compelling behavioral differences (i.e., are residents of city X more violent?) or political distinctions (i.e., this law in City Y impacts residents in a tangible way).

Our findings provide reinforcement for the continue adaptation of general place-based crime prevention strategies. Interventions such as problem-oriented policing or crime prevention through environmental design (CPTED) strike the same balance of being generally adaptable across a wide-range of places but also malleable enough to account for unique characteristics of places which facilitate crime (Goldstein, 1979, 1990; Hinkle et al., 2020). Another example is hot spots policing strategies which have been found to be effective at reduce crime by targeting the concentration of crime at a small number of micro-places across very different cities (see Braga et al. 2020). Our findings also suggest policy not move completely past the importance of higher-order units such as tracts or those representing neighborhoods. For a few cities in our study, tract-level variance was higher than expected. Much variability occurs at micro-places but to unlock the next wave of crime reduction these larger units of analysis are critical to understand.
There were several limitations to this study. Due to the large number of options for spatial units of analysis even within cities there is always subjectivity to the selection of a unit of analysis to study. There are inherent concerns when micro-units (often street segments) far exceed the number of crimes being analyzed (see Andresen & Linning, 2012; Bernasco & Steenbeek, 2017). While we address this issue for our measurement of Gini coefficients the broader concern permeates all analyses on spatial variability. Due to the large number of places when examining micro-places and rare crime events this could influence the magnitude of which variability is observed between these units. Furthermore, our findings are limited to variance estimates of robbery. Other crime types were not examined which could influence our observed estimates of variance. The number of cities observed is only a small fraction of the locations with populations which exceed 100,000 residents. We attempted a systematic approach, but this cannot account for the fact that while growing, the number of cities which provide public data is still small.

Our study compliments prior crime and place research while offering excellent avenues for future research to build upon. The modest differences among the estimates of robbery variability between the eight cities is surprising and an avenue for future research. For example, there are massive differences between the cities in the population and number of units of analysis. Despite the large range for these two characteristics between the cities, variance estimates differed slightly. Future research should continue to explore additional cities and explanations for this variance. Additionally, questions arise as to whether “shifting” the units down from blocks to street segments and tracts to block groups would observe similar estimates. Further, future research will need to
incorporate different spatial weighting processes to better understand the proximal influences within and between units. Replicating our approach, future research should incorporate more variables such as different spatial lags and or city characteristics to the models. Comparing estimates between units such as street segments versus blocks or street segments within blocks are additional possibilities. Opportunities also exist to incorporate models which can provide a more sophisticated treatment of these complex spatial-temporal processes.

Overall, estimates of the spatial variability of robbery within and between eight U.S. cities are generally aligned with previous research on the spatial distribution of crime at micro-places. Our study provided additional evidence to support the law of crime concentration and a new framework to assess this seminal proposition. The effect of cities was small but not negligible. In general, this component of the law of crime concentration is striking to consider even years after its proposal. That despite the wide range of differences for cities the actual spatial distribution of crime is similar. An abundance of methods and techniques for selecting units of analysis exist making traditional comparisons of these variance estimates difficult. This study systematically analyzed robbery variability within and between eight U.S. cities. While micro-places account for most of the total spatial variability, the contribution of larger spatial aggregations is still critical to understanding where crime happens in place.

References


CHAPTER 5

BEST PRACTICES FOR ILLUSTRATING THE SPATIAL VARIABILITY OF CRIME: RE-IMAGINING THE CRIME MAP\textsuperscript{19}

\textsuperscript{19} Spencer, M. D. To be submitted to Cartography and Geographic Information Science.
Abstract

Objective

Many methods exist in mapping software to illustrate the spatial variability of crime. Yet, the use of maps from recent research does not parallel cartographic advancements. This study examines the current use of maps in research of the spatial variability of crime and presents innovative methods for illustrating crime across multiple geographic levels.

Data/Methods

To examine the current use of maps, data from studies on the spatial variability of crime were used. Further, using crime data from Atlanta, GA, estimates of spatial variability were illustrated using dynamic maps.

Results

No prior use of dynamic maps to illustrate the spatial variability of crime were observed. Multiple open-source methods are discussed and presented on how to create dynamic maps. These types of maps allow for a nuanced illustration of crime variability across multiple geographic levels.

Conclusions

Presently, maps are underutilized in research on the spatial variability of crime. To properly illustrate the spatial variability of crime, methods which incorporate multiple geographic levels are necessary. Dynamic maps are an effective method that should be embraced by future research.
Introduction

Criminal behavior and subsequently crime is explicitly linked to place. Crime is a measurable outcome directly influenced by places within space; all of which can be visualized by maps. The connection between geography and crime is hardly new, nor is the use of maps for illustrating it (Chainey 2021; Chainey & Ratcliffe, 2005). When compared to tables full of statistics and visuals such as bar charts or line graphs, maps can be more effective forms of communication when well designed (see Brewer, 2016; Monmonier, 2018; Peterson, 2021; Tufte, 2001). Maps are particularly useful for communicating how crime varies across space by revealing its non-uniform distribution and clustering (Anselin et al., 2008). Within criminology, maps have been used to study and illustrate crime for over 200 years. The earliest examples of crime maps were quite simplistic yet informative for their time (see Guerry, 1833; Mayhew, 1862; Quetelet, 1831 [1984]). Within the interest of crime and place research, these historical maps were the first indications that crime was not randomly oriented across space.

Despite their earlier use during the Chicago School (see Burgess, 1925; Shaw and McKay, 1942), the use of maps in criminology became mainstream with the growing interest in hot spots policing (Sherman et al., 1989; Sherman & Weisburd, 1995). Research of hot spots can loosely be attributed from the late 1980s to the early 2000s (Chainey & Ratcliffe, 2005). Technological improvements in data collection and mapping capabilities are a key reason why hot spots were extensively studied during this time. Additionally, hot spots were of use to law enforcement agencies and of public curiosity, furthering their reach. The dissemination of hot spots information often came in the form of maps which could appropriately illustrate them rather than through
descriptive language. Even before the advent of modern computing and map making software, creating maps during this period was much easier compared to the hand-drawing techniques of the past.

Crime maps are still common; however, their use appears to have lessened after intense research on hot spots towards more advanced methods that rely heavily on numerical descriptions (see Ratcliffe, 2010). In their place, spatial measures of crime patterns and measures of statistical concentration such as the Lorenz curve and Gini coefficient have dominated much of the recent literature. Additionally, a focus on micro-places, which often number in the thousands compared to observed crime, lead to visualization issues. While still being used, the designs of maps have changed little from early research. Journal restrictions are partly responsible, but a lack of interest may also be a contributing factor. In fact, across multiple scientific fields, the advancements made in the discipline of cartography rarely translate to academia (O’Sullivan & Unwin, 2010). Rather, outside groups such as news organizations appear to be adopting the new trends in mapping. Whatever the explanations, maps have been and still are an important method for communicating information about crime. Their continued use will be instrumental in retaining interest and attracting new researchers to the subject.

Two research goals frame this study. One, to understand the recent use and to promote the continued use of maps in criminological research. Two, to discuss and present innovative mapping techniques by using the spatial variability of crime as an example. These research goals will be addressed by using data from a systematic review on the spatial variability of crime as well as public crime incident data for the mapping components. How maps are used, and their design will be analyzed from the studies
included in the systematic review. Then, innovative techniques for mapping crime will be presented using crime incident data from Atlanta, GA. Finally, how maps can be potentially integrated into the current structure of peer-reviewed journal publications will be discussed.

The History of Crime Mapping

The use of maps for crime research is older than the field of criminology. Interest in the geographic analysis of crime has varied from the early 1800’s to present with much of the relevant research utilizing maps. Maps are often used to familiarize the reader to an area of interest or for elementary descriptive analyses. Following the periods as defined by Chaineý and Ratcliffe (2005), the history of crime mapping and to a broader extent crime and place research, can be placed into three periods: the Cartographic school, the Chicago school, and the GIS school.

Before the establishment of criminology as a discipline, European researchers were interested in the distribution of crime. This period is called the cartographic school as much of the research was descriptive and contingent on communicating information using basic thematic maps to government agencies. In France, Guerry (1833) examined the spatial variation of violent and property crime across jurisdictional divisions of the country. Guerry’s thematic maps were shaded using grayscale to illustrate areas of lower and higher crime rates based on urban-rural divisions. Though hardly useful by present standards, Guerry’s research is one of the earliest examples of a crime map. Around the same time as Guerry’s research, Quetlet (1842), combined the visual benefit of maps with statistics; a precursor to much of the work that would follow. Mayhew (1862) is another historical example of how maps were used to study crime. In his research of London,
Mayhew (1862) published maps that showed patterns of offending across the city. Similar work from Mayhew mapped intensity levels of crime across England and Wales by county.

After a lull resulting from diminished interest for analyzing crime geographically, occurred perhaps the most-well known period of research that utilized maps: the Chicago school. During this time, much of the research was focused on understanding crime at the meso-level using neighborhoods. Researchers such as Burgess (1925), and Shaw and McKay (1942) had access to more finely detailed data than what was available during the cartographic school. Therefore, they were able to analyze crime at a finer spatial level which shifted the research away from macro-units such as countries to cities and their sub-units. Combining land use and socioeconomic data for Chicago, Burgess (1925), examined how crime among other factors transitioned across the city. To illustrate his work, Burgess created the concentric model, comprised of five zones. Each zone represented a portion of Chicago with corresponding socio-demographic characteristics including observed crime rates. Shaw and McKay (1942) later extended the concentric model by hand mapping thousands of addresses for the locations of juvenile delinquent’s homes. They did this for multiple cities and observed consistent patterns of offending with concentrations of crime in certain areas. The zones with the highest concentrations of crime were located towards the city center. Much of the maps created during the Chicago school were intended for academics and city agencies tasked with reducing crime and addressing juvenile delinquency.

The GIS school of crime mapping is more loosely defined but can largely be attributed to the advent of geographic information systems (GIS) and other computer
advancements. This period between the 1970’s and early 2000’s is when the development of mapping software and data with geographic attributes allowed for novel research. Hot spot analysis and by extension, hot spot maps, were a very popular technique during this time and often used by law enforcement agencies (Ratcliffe, 2010). Hot spot maps illustrate a more localized fluidity of crime based on levels of concentration. They also can only be accurately created using computers; a stark contrast to the hand-made maps of prior. Numerous other techniques flourished during the GIS school that are the foundation for much of how crime maps are created today such as certain design principles involving color and projecting geographic data onto a screen (see Chainey & Ratcliffe, 2005; Walker & Drawve, 2018). Maps during this period were often used to disseminate crime information to the public or law enforcement agencies. Therefore, the maps were designed to orient users quickly to recognizable features in the area of analysis.

A representation of the modern period of crime mapping can be described using a relatively new term, geocomputation. This term extends the ‘quantitative geography’ beyond the use of spatial statistics by focusing on creativity and experimental methods that appeal to diverse audiences (Lovelace et al., 2019; Openshaw & Abrahart, 2000). Another important aspect of geocomputation is reproducibility which often occurs in the form of open-access data and accompanying programming code (e.g., R, Python, SQL). A Geocomputation school (2010-present) fits well with recent crime and place work that frequently incorporates novel methodology beyond that of hot spot analysis (see Hipp et al., 2021; Quick, 2019). However, equally sophisticated maps typically do not accompany the innovative statistical analyses observed across recent research. Current
cartographic technology allows for crime maps to expand beyond static 2D computer images to 3D and even 4D (including a time component). Other creative mapping techniques exist but are rarely, if ever, utilized in crime and place research of the last decade. The disconnect between the methods and mapping techniques used in the Geocomputation school are of central concern for this paper.

**New Methods of Map Design**

At present, mapping software commonly used is proprietary such as Esri’s suite of software. Other, open-source options exist such as QGIS and the R and Python programming languages. Regardless of the chosen software or programming language, at present, most allow for the researcher to quickly create appealing maps. A good-looking map does not always translate to a useful one, though (see Brewer, 2016).

Extending beyond the traditional design elements of maps such as color or scale, this paper aims to focus on how a map is visualized from the researcher to the user. For example, static maps are those that are observed among all current and past crime and place research. Static maps are non-interactive and are images of maps created using some software. A dynamic map, a central topic of this research, is interactive in some form. Dynamic maps can have multiple layers that can be turned “on” or “off” by the user for post-production analysis. They can also have a zoom or a time feature that allows for direct interaction with the map and data. How crime varies across different geographic levels can be easily visualized using a dynamic map. To do the same visualization using static maps would require multiple maps for each spatial level. Additionally, fine details are often overlooked or ignored when using static maps. More
detail can be added to dynamic maps as they have the capacity for zooming or panning which interactively changes the geographic view as dictated by the user.

The printing process of academic journals prevents the use of non-static maps in publications. However, as many journals have adopted online versions and advocate for open-data and code availability, appendices, and external extensions to sites such as GitHub are becoming more common. Linking to dynamic maps from within online publication versions is a possibility. Exploiting this possibility can advance crime mapping and the crime and place field broadly by visualizing difficult-to-understand topics such as spatial variability.

**Data and Methods**

**Present Study**

Ratcliffe (2010) provides one of the most recent examples of advocacy for the continued use of crime maps and insights into their future use (see also Kindynis, 2014). One of the many important points Ratcliffe made is that while maps are relatively easy to create using computer software, often their design is limiting, and the user is left confused. As a growing body of research has found that crime varies by spatial level (O’Brien & Winship, 2017; Schnell et al., 2017; Steenbeek & Weisburd, 2016), static maps are ill-suited for illustrating such hierarchical variances. A solution for increasing users’ understanding of the map is to incorporate a dynamic design. This study has two research goals that are each framed by the primary objective to observe the spatial variability of crime using different mapping techniques.

To address the first research goal of the present study, an additional examination of the studies identified in the systematic review by Spencer (2022) was conducted. In the
systematic review, relevant research on the study of the spatial variability of crime from 2010-2019 was identified and analyzed. Presently, those studies which utilized maps from Spencer (2022) were further analyzed on a few criteria based on their utilization of crime maps. Whether a map was used, the type of map used, design features, and the existence of links to external maps among others are examples of review criteria.

The second research goal is addressed by the creation of examples of dynamic maps using appropriate packages within the R statistical environment. Publicly accessible crime data for Atlanta, GA from 2015-2019 was used to create measures of variance across multiple spatial levels. Local tests of autocorrelation and variance estimates were calculated at the census blocks, and census tracts. Dynamic maps were created that enable the user to interact with the data and see the distribution of crime at each spatial level within a single map. Specifically, these maps help illustrate the hierarchical spatial variability of crime across multiple units within Atlanta. Attempting the same process with static maps would require multiple maps for each unit such.

**Data**

The data on map usage for this study comes from the Spencer (2022) systematic review of research on the spatial variability of crime. Studies that were captured in the review were examined based on their use of crime maps. To create the dynamic crime maps, crime incident data from Atlanta between 2015-2019 was used. Atlanta was selected out of convenience to the researcher. The time frame was selected to ensure a large enough sample was available for mapping purposes.

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20 This data was obtained from the Atlanta Open Data Portal (https://www.atlantapd.org/i-want-to/crime-data-downloads). Geographic data for Atlanta was downloaded directly from the U.S. Census TIGER/Line Shapefiles database using the Tigris (version 1.0) package into R where the appropriate shapefiles were created (Walker, 2020).
Mapping Strategy

Many methods exist for creating dynamic maps. This paper focuses on using the open-source R statistical environment for creating dynamic maps. Specifically, the Leaflet (version 2.0.4.1), Tmap (version 3.3-1), and Shiny (version 1.6.0) packages are used to create maps and web-based dashboards (see Chang et al., 2021; Cheng et al., 2021; Tennekes, 2018). In each application, the user has the ability to interact with the crime data and visualize crime variability across multiple spatial levels and units.

Results

Research Question 1

Key features regarding the use of maps were examined using the 11 studies identified by Spencer (2022). The majority (82%) of the studies utilized maps. In sum, 81 maps were used and on average nine maps were used per study by those which used them. No use of dynamic maps was observed either within the studies or as supplemental material. A little less than half (47%) of the maps were in color or included color components. Seven of the nine (77%) studies used multiple maps to illustrate levels of concentration or variance per unit; thus, highlighting the difficulty of illustrating nested spatial variance with static maps. The two other studies which used maps did so to illustrate spatial units.

To further examine the use of maps from recent spatially related research, a simple random sample of 10% (n = 53) was taken of the original 524 (with the 11 reviewed studies excluded) studies identified through database searching by Spencer (2022). Though these studies were not included as part of the systematic review they are a robust representation of spatial research conducted from 2010-2019. Of those sampled,
75% used maps with an average of 4 maps per study. Maps that incorporated color were used slightly less compared to black and white maps. Studies from geography journals often included more maps and maps that utilized color or other unique designs such as raster images and 3D designs. No temporal trend was apparent that indicated an increased or decreased use of maps across the study period.

These findings indicate maps are commonly used by studies dedicated to analyzing spatial variability as well as the broader research on crime and place. Geography journals appear to be more accepting of detailed maps and the quantity included per study. Our results also highlight the difficulty of illustrating the concentration and variability of crime using a single map. Of particular difficulty are attempts at illustrating these phenomena at the micro-scale where many units are present and can overwhelm the map. In no case were dynamic maps used to illustrate crime across multiple levels and units. Static maps can also only visually communicate so much information and numerous maps are often required to illustrate concepts such as hot spots across multiple units.

**Research Question 2**

In this section, examples of crime maps (static and dynamic) are presented and discussed. Figure 5.1 contains three maps of robbery by census blocks in Atlanta from 2015-2019. The first map (left-most) is of robbery counts using a Fisher-Jenks binning method (Fisher, 1958). Using the same method, the second (middle) map is of variance estimates per block in the city (see Leckie et al., 2019 for discussion on how estimates of variance were calculated). Lastly, the third map (right-most) is of hot and cold spots
determined by the Gi* test of spatial autocorrelation (Ord & Getis, 1995). The maps in Figure 5.2 are analogous to those in Figure 5.1 but for census tracts rather than blocks.

The focus of these maps is not the method for analyzing the spatial distribution of robbery, but the presentation of results. The maps in Figures 5.1 and 5.2 are typical examples that can be seen in much of the prior research. While useful to a degree, data interpretation at a finer level is difficult if not impossible. Zooming in on the images often will distort them, thus, their usefulness is limited. For example, when viewing the map of robbery hot and cold spots by block, the user is left ill-informed of any detail as to which blocks contain high levels of crime and exactly where they are located. Only broad geographic clusters are readily apparent. To some degree the level of interpretability provided by these maps is sufficient for general conclusions of where crime is occurring at the city-level despite being analyzed at a much smaller-scale. Often, when more detail is necessary accompanying “zoomed-in” or subset maps such as those in Figures 5.3 and 5.4 are provided.

The maps in Figures 5.3 and 5.4 are images captured from dynamic maps of robbery in Atlanta. These images illustrate the nuances that dynamic maps offer with the addition of a street network layer that assists in identification akin to Google Maps. Figure 5.4 offers more detail with the inclusion of a marker for Mercedes Benz Stadium, a popular sporting arena in Atlanta. A popup marker appears over one of the identified blocks that contains more information about the levels of robbery for that block. These options, while possible on static maps, can easily be overwhelming when occurring hundreds if not thousands of times.
Figure 5.1 Choropleth maps of robbery incidents by census block in Atlanta (2015-2019)
Figure 5.2 Choropleth maps of robbery incidents by census tract in Atlanta (2015-2019)
The maps in Figures 5.3 and 5.4 are images captured from dynamic maps of robbery in Atlanta. These images illustrate the nuance that dynamic maps offer with the
addition of a background overlay of the street network that assists in identification of areas in the city; akin to Google Maps. Figure 5.4 offers even more detail with the inclusion of a marker for Mercedes Benz Stadium, a popular sporting arena in Atlanta. Additionally, a popup marker appears over one of the identified blocks that contains more information about the levels of robbery for that block. These options, while possible on static maps, can easily be overwhelming when occurring hundreds if not thousands of times. For example, Atlanta has 6,735 census blocks and 139 tracts. It would be impractical to display information for each block using a static map.

A dynamic map allows for zooming and the ability to display information when needed such as by clicking or hovering over a block. Additionally, with the incorporation of background overlays (called tiles in Leaflet; the package used to create these dynamic maps) endless detail can help familiarize the reader to locations within the map. The OpenStreetMap background used in Figures 5.3 and 5.4 is free to use and like those of popular mapping software such as Google Maps. The familiarity of these type of maps helps users navigate them easily and ultimately gain greater insight into the phenomenon being explained.

Perhaps the most limiting factor of static maps is the lack of multi-level incorporation. For example, to illustrate the spatial variability of robbery in Atlanta separate maps for estimates at the block and tract were necessary as evident by Figures 5.1 and 5.2. A more practical and useful method is to create a map that has both estimates on the same map. Thus, a dynamic map with the ability to turn layers “on” and “off” is highly useful. An image from a dynamic map that has this feature is presented in Figure 5.5. On the right-side of this image a feature is present that allows the user to select
which layer (one, both or none) they want to view. The option of highlighting certain units within the layers correspondingly switches and is evident in Figure 5.6 by the presence of a dashed border. This feature helps clarify what units are within larger units. For example, with both layers turned “on”, a user can view which blocks are located within which tracts. Therefore, in this example it becomes clearer that many tracts are not completely inundated with instances of robbery, yet certain blocks within tracts are responsible for the high rates. The tract highlighted in Figure 5.6 is not identified as a hot spot, yet multiple blocks with the tract are. This phenomenon of high crime concentration and variability has been well supported in prior research (Eck et al., 2017; Haberman et al., 2017). Yet, multiple maps are routinely required to illustrate the hierarchical nature of crime variability; often, leaving the user to constantly browse one before switching back to another.

Figure 5.5 Image of dynamic map with multiple layers
Figure 5.6 Image of dynamic map with highlighted area (dashed border)

Figure 5.7 Image of Shiny dashboard

Figure 5.7 is the final image presented. This figure is of an image of a Shiny dashboard. This example of a basic dashboard contains a dynamic map just like those previously shown. The difference being that a Shiny dashboard is designed to be hosted
online and includes many more options beyond that of the dynamic maps shown in Figures 5.3, 5.4, and 5.5. The options for a Shiny dashboard are overwhelming and not discussed in-depth here (see Chang et al., 2021 for more details). One example is the option for post-processing data such as linking user selections to dynamic graphical displays like histograms. It should be noted that the other dynamic maps presented are also hosted and viewable using an internet browser, yet they are less like an interactive website and more like a single webpage (see footnote for URLs to dynamic maps). While the options for post-processing and other characteristics of a Shiny dashboard are impressive the skill required to create one can become too time-intensive and beyond what is necessary for most researchers. The example provided here only includes the addition of a banner title alongside the dynamic map. During the process of creating the dashboard, it was realized the time committed and possibility of hosting fees due to the processing power required for spatial tasks was too great. Therefore, for this study the development of the dashboard was not pursued further nor is it hosted online.

Discussion

Interest in crime and place research has grown immensely in the past few decades. While maps are still commonly used in the related research, rarely are newer cartographic techniques embraced. The likely culprit is journal restrictions or programming and software expertise required to create dynamic maps. Other barriers may also exist that prevent the adoption and use of some of the newer mapping techniques. However,
addressing many of those issues discussed in this paper are relatively straightforward and can greatly enhance how hierarchical relationships of crime and space are illustrated.

At present, peer-reviewed journals are often printed and to the author’s knowledge do not have the integrated capabilities for including dynamic maps within articles posted online. Options do exist to accommodate them, though. The use of supplementary links to external sites where dynamic maps are hosted online is one such example. An important caveat is the intended audience. Certain audiences such as law enforcement and academics respond to or expect different types of maps. Similarly, the amount of time required to create more advanced maps is an important consideration. The paradox of creating maps is that they will never be perfect, but we can strive to utilize the most recent advancements in the field of cartography. While the dynamic maps displayed in this study required a lot of programming to create, the process to do so is similar to learning a new statistical method; it requires time and practice. In the short term, dedicating time to develop these skills may seem like a loss on investment. Yet, it should be stressed that dynamic maps are an asset that will likely become more commonplace as technology is further incorporated into research including the dissemination of findings. Continuing the use of maps and including newer cartographic techniques will serve crime and place research well.

**Conclusion**

In this study, the use of maps in research on the spatial variability of crime from 2010-2019 were examined. Additionally, new methods for creating maps and disseminating research findings using these methods were discussed. At present, the current and past use of maps in crime and place research can be improved by adopting
newer cartographic techniques. The benefits of adopting these techniques have been discussed and suggestions made for their use.

Within crime and place research, the transition to becoming more technologically integrated is prudent for researchers recognize and embrace. Accepting and utilizing these advancements will make research findings more accessible to relevant stakeholders and potentially grow interest among younger generations of crime and place researchers. As evident by the findings in this study, static maps have a long history in criminological research and will continue to do so. However, technology presently allows for much more advanced iterations of maps which can communicate more information via a more accessible medium. As peer-reviewed journals continue to transition resources online and expand beyond printed copies, limitations of creating and disseminating maps are decreasing. The methods to create dynamic maps discussed in this article are but a few of the many options available. All of which, can hopefully inspire a new generation of crime cartographers, and strengthen relationships between researchers and practitioners.

References


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CHAPTER 6

CONCLUSION

This dissertation, comprised of three related articles, sought to examine the phenomenon of spatial variability of crime. Specifically, a systematic review of the relevant literature, a proposed modeling strategy, and innovative mapping techniques were conducted to further understand spatial variability. For more on those findings refer to their respective chapters. A recap of each of these study’s findings can be stated concisely:

1. A lack of cohesiveness regarding methodological choice and the selection of units of analysis exists in the crime and place literature.

2. The spatial variability of crime between cities is remarkably similar. Micro-units account for the largest proportion of total crime variance. Ultimately, the variability estimates calculated suggest city’s do not have a large effect on shaping the spatial distribution of crime.

3. In crime and place research, maps are still commonly used to illustrate the distribution of crime. Visualizing the spatial variability of crime requires multiple static maps. Mapping techniques such as dynamic maps address this issue by illustrating crime across multiple units within a single map that is interactive.

Important considerations for any spatial analyses of crime are the selection of a unit(s) of analysis and appropriate methods. These considerations have been discussed in great detail throughout this work. It is these issues that ultimately guided the primary goal of this dissertation: examining and refining the concept of spatial variability.
In this dissertation the concept was defined and studied in three unique ways. Each study’s findings have contributed to crime and place literature by furthering our understanding of spatial variability as a unique concept worthy of further attention. Particularly, comparisons were made between crime concentration and spatial variability. It is recognized that both concepts are important for framing how crime is distributed across space and in some areas more than others. However, to understand the true spatial context of crime in a city a test of spatial variability is required. That is, for example, multiple units of analysis are required to study how some neighborhoods can be identified as hot spots with relatively few micro-units within them also being identified as such. Any combination of within and between unit comparisons are sufficient tests of the concept.

The Future

The findings of this dissertation support the use of multiple spatial units of analysis while recognizing the considerable role micro-places have in related research. Larger units of analysis such as neighborhoods, while still important, are relatively limited by their scope of inference. More so, between-city estimates of variability are similar. These findings hint at a few considerations for future research to expand upon. First, future research should continue to apply new methodological approaches while replicating past ones for an array of crimes at various spatial scales. Second, as research on crime concentration and spatial variability become more refined, areas of focus should expand beyond urban areas. Each of these considerations are discussed further.

As observed from the findings of the systematic review, no consistency for selecting units of analysis or methods exists. This point is not made for the opinion that a
typology should exist with little deviation. However, a clear lack of replication and purposeful methodological selections is evident. Future research should continuously test the boundaries of what defines a micro-place and neighborhood. Often, pre-determined boundaries are used for geographic delineation. Other processes are available such as grid cells that can be created using different inputs such as social characteristics to determine their size and quantity. A downfall with this method is their usefulness to law enforcement may be diminished compared to units commonly used. Additionally, as increased volumes of data become easily accessible crime and place researchers will soon be met with a question of what defines a micro-place? Is it street segments, addresses, census blocks, or each of these? Is it possible that data can become detailed enough where crime can be analyzed at single addresses vertically (e.g., by apartment floor)? As urban areas continuously evolve, so should our definitions of place.

Another question that will inevitably become a topic of increasing interest is what combination of units is best, if one exists? Like the units used in the second study within this dissertation, are polygon units that nest neatly preferred? Or is it some combination of multiple micro-units and a meso-units? Aside from a few studies, these questions are largely still unanswered. Related, is whether a different set of units in the same city such as street segments and census block groups will have similar estimates of variability compared to blocks and tracts. Using this scenario, is it a case of variance estimates shifting to similar units, or will they significantly change?

Pertaining to the analysis phase of research, like unit choice, no clear methodology to measure the spatial variability of crime is apparent. Many options are available, with some being more appropriate than others. Future researchers should also
concern themselves with the use of covariates of spatial variability. While this dissertation did not analyze covariates in its models, crime and place theories often explicitly link characteristics such as race, economic status, and education levels, among others to place. These covariates likely serve an important role in understanding why certain locations are persistently crime prone and distributed in certain patterns. Likewise, covariates such as land use are often easily obtainable and spatially informed for many areas in the U.S. and may add more context to this area of research.

Beyond unit and methodological choice, are decisions about what crime(s) and in which cities or non-urban areas to analyze. A historical query that has yet to be sufficiently addressed is whether crime and place research findings apply to suburban and rural areas. I advocate for expanding research beyond urban areas, particularly major cities in the U.S., to increase the applicability of research findings. Examining the spatial of variability of crime in non-urban areas will undoubtedly present methodological challenges such as edge effects and a lack of quality data. This task is becoming easier though as more data for non-urban areas is being collected and increasingly open-source
REFERENCES


Woolredge, J. (2002). Examining the (ir)relevance of aggregation bias for multilevel studies of neighborhoods and crime with an example comparing census tracts to official neighborhoods in Cincinnati. *Criminology, 40*, 681-710.
APPENDIX A

ELIGIBILITY CHECK SHEET

1. Document ID __ __ __ __

2. First author last name: _______________

3. Study title: _______________________________

4. Journal name, volume and issue: _______________________________

5. Coder’s initials __ __ __

6. Date eligibility determined: ______________

7. A study must meet the following criteria in order to be eligible. Answer each question with a “yes” or a “no”

a. The study is an examination of the spatial variability of crime. _____

b. The study utilizes spatial methodology. _____

c. The study is written in English. _____

If the study does not meet the criteria above, answer the following question:

a. The study is a review article that is relevant to this project (e.g., may have references to other studies that are useful, may have pertinent background information) _____

9. Eligibility status (circle one): Eligible, Not eligible, Relevant review
APPENDIX B
CODING PROTOCOL

1. Document ID: __ __ __ __

2. Study author(s): ________________

3. Study title: _______________________

4a. Publication type: ____

   1. Book

   2. Book chapter

   3. Journal article (peer reviewed)

   4. Doctoral dissertation

   5. Government report

   6. Police department report

   7. Technical report

   8. Conference paper

   9. Other (specify)

4b. Specify (other) ________________

5. Publication date: ________________

6a. Journal name: ________________

6b. Journal volume and issue: ________________

7. Date range of research (when research was conducted):

   Start: ______
Finish: __________

8. Source of funding for study: ________________

9. Country of publication: ________________

10. Date coded: ________________

11. Coder’s initials: __ __ __

Background Information

12. Was this study original or a replication? ________________

13. What theory was used to provide background information? ________________

14a. What type of crime was analyzed? (Select all that apply)

1. Predatory crimes against persons (sexual assault, robbery, homicide)

2. Predatory crimes against property (vandalism, auto theft)

3. Illegal service crimes (prostitution, selling drugs)

4. Public disorder crimes (disorderly conduct, drunkenness)

5. Vehicular/traffic offenses

6. Status crimes

7. Drug use

8. Overall crime/disorder

9. Other (specify)

14b. Specify (Other) ________________

15. Where was the crime data retrieved? ________________

16. Is the crime data available open access? ______

17. What is the total sample size of analyzed crime? ________________

18. Is the crime aggregated? ______
Descriptive Statistics

18. Was a Lorenz curve used? ______

19. Was the Gini coefficient used? ______

20. Was a statistical test for concentration performed? (i.e., 80/20). ______

21a. Was a descriptive graph/figure used to represent spatial concentration other than the Lorenz curve? ______

21b. If yes, what type of graph or figure was used? __________________

22. Were maps included? ______

23. How many maps were included? ______

24. Are any of the maps in color? ______

Spatial Methodology

25. What spatial level of analysis was examined? (Select all that apply)

   1. Micro
   2. Meso
   3. Macro

26. What were the spatial unit types? (Select all that apply)

   1. Lines
   2. Polygons
   3. Points
   4. Raster

27a. What were the spatial units? (Select all that apply)

   1. Street segments
   2. Addresses
3. Blocks
4. Tracts
5. Neighborhoods/Community areas
6. City-wide
7. Other (specify)

27b. Specify (other) __________________________

28a. What type of test for spatial autocorrelation was performed?
   1. Global (e.g., Moran’s I, Geary’s C, General G-Statistic)
   2. Local (e.g., Local Moran’s I, Getis-Ord Gi and Gi *)
   3. None
   4. Other (specify)

28b. Specify (other) __________________________

28c. Indicate the test for spatial autocorrelation performed. ________________

29a. Was a spatial weights matrix mentioned? ______

29b. If yes, what type was used? ______________

30a. Was a multi-level model used? ______

30b. If yes, what type? __________

31a. Was a spatial regression model used? ______

31b. If yes, what type? _______

32a. Were hot spots analyzed? ______

32b. If yes, what method was used to calculate the hot spots? _________________

33a. Were spatial buffers or distance lags used? ______

33b. If yes, what was the distance(s) used? ______________________
34a. Was a point-pattern analysis performed? (e.g., Ripley’s K, Nearest neighbor) 

34b. If yes, what type of point-pattern test was performed? 

35. What statistical software was used for the analysis? 

36. What spatial/mapping software was used for the analysis? 

Conclusions

37. What were the estimates of the spatial variability of crime?

1. Micro level 

2. Meso level 

3. Macro level