SEXUAL ABUSE AND ASSAULT AGAINST MINORS:

A SPATIAL APPLICATION OF ROUTINE ACTIVITY THEORY

by

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ABSTRACT

Recent advances in criminological theory have changed the way we approach age-old questions of criminality. Routine activity theory, hotspots analyses, and spatial-statistical models have become popular methods of investigating criminal phenomena. This study tests the applicability of spatial analyses and routine activity theory by examining the relationship between a geographically-measured lack of guardianship composite score and the occurrence of child sexual abuse (CSA) and sexual assault perpetrated against minors (SAAM). Moran's I, single kernel interpolation, dual kernel interpolation, and spatial lag regression are used as methods of analysis for this study. Strong evidence of spatial clustering is observed and a significant relationship between the lack of guardianship composite score and the spatial lag of CSA and SAAM incidents is identified. These findings further support routine activity theory and demonstrate the need to continue integration of spatial-statistical techniques with traditional criminological theory.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

RAT	Routine Activity Theory
CSA	Child Sexual Abuse
SAAM	Sexual Assault Against Minors
SA	Sexual Assault
ACS	American Community Survey
UCR	Unified Crime Reports
NCVS	National Crime Victimization Survey
NIBRS	National Incident-Based Reporting System

CHAPTER ONE: INTRODUCTION

On November 29th, 2017 Dr. Larry Nassar pleaded guilty to three counts of first-degree criminal sexual conduct in Eaton County Circuit Court (Rosenblatt, 2017). The world was shocked that a doctor for the Olympic gymnastics team could be guilty of such horrific crimes. Decades earlier, though the defendants were ultimately acquitted, Americans were entranced by the criminal proceedings of one of the largest and most expensive court cases in U.S. history as hundreds of allegations of child sex abuse were made against the owners of a child care center in what is now known as the McMartin Preschool case (Crewdson, 1988). Americans, both then and now, clamor for an explanation as to how an individual could descend to the level of sexually abusing a minor. Researchers from various fields began investigating the variables that could explain the motivations for offenders to engage in this type of deviant sexuality, and what factors placed children at increased risk for victimization (Finkelhor, Shattuck, Turner, & Hamby, 2014; Olafson, Corwin, & Summit, 1993). Although new to many who had not conceived of the possibility of children being taken advantage of in this way, the question was nothing new to criminologists who had been attempting to answer similar questions for hundreds of years as they pertain to other types of criminal and deviant behavior. One of the oldest and most difficult questions regarding the sexual victimization of children is how often it occurs. Estimates are difficult to establish, but recent studies suggest nearly 25% of girls and 5% of boys are sexually victimized by the time they reach adulthood (Finkelhor, et al., 2014; Pereda, Guilera, Forns, & Gómez-Benito, 2009).

Rooted in many criminological studies are complex statistical models attempting to understand how a wide range of variables interact with a potential outcome. Criminologists have long sought to understand what factors would successfully forecast criminal behavior. In the case of sex crimes perpetrated against minor children, psychological researchers have attempted to explain how offenders are motivated to engage in this type of behavior (Finkelhor, 1984; Hall & Hirschman, 1991; Marshall & Barbaree, 1990; Ward & Siegert, 2002). Others have specifically analyzed what characteristics make children more vulnerable to sexual victimization (Finkelhor, 1979). While offender motivation and individual-level victim risk characteristics are necessary elements, few researchers, if any, have considered the possibility of environmental influence.

Traditional criminological theory focuses on the individuals involved in criminal events, most often the offenders. Throughout the 1980s and the 1990s a new wave of environmental criminologists shifted that emphasis toward a consideration of the physical characteristics of location and place as they related to victims and perpetrators (Brantingham & Brantingham, 1981). This emergent field emerged from the early works of Shaw and McKay (1942) who considered the possibility of crimes occurring more densely in certain areas that were environmentally distinguishable from others. Researchers later expanded on those foundations through their own theoretical interpretations of environmental influence. One notable area of expansion was hotspots research (Sherman, Gartin and Buerger, 1989; Sherman & Weisburd, 1995).

Hotspots were defined as areas of dense criminal activity and were historically identified using point maps. With technological advancements and the proliferation of computer software, hotspot measurement practices have developed into more accurate and informative kernel interpolations (Chainey, Thompson, & Uhlig, 2008). Few, if any studies have identified or measured hotspots for incidents of child sexual abuse and sexual assaults perpetrated against minors. The identification of hotspots allows researchers to ask questions about environmental influence. If crimes cluster in hotspots, the next logical question is why? Routine activity theory (Cohen & Felson, 1979; Cohen, Felson, & Land, 1980; Cohen & Cantor, 1980) provided one such prospective explanation.

Routine activity theory (RAT) gave a more formal shape to the idea of criminogenic places by recognizing the convergence of motivated offenders, suitable targets, and lack of guardianship in physical space in order for crime to occur. Eck and Weisburd (1995) later added the necessary element of place to the original three elements. They furthered the environmental discussion by questioning what environmental factors may have encouraged the convergence of offenders and targets in space. RAT has been repeatedly tested for a variety of criminal behaviors (see Jensen & Brownfield, 1986; Kennedy & Baron, 1993; Sampson & Wooldredge, 1987). As such this study is primarily concerned with two questions: first, to determine if reported incidents of sexual abuse and sexual assault perpetrated against minors cluster to form hotspots; second, to test the applicability of routine activity theory as a spatial predictor of the likelihood of sex crimes perpetrated against minors and children, particularly as it pertains to a community-level measure of lack of guardianship.

CHAPTER TWO: PREVIOUS LITERATURE

Sexual crimes committed against minors in the form of child sexual abuse (CSA) or sexual assault perpetrated against minors (SAAM) have been of increasing concern in recent decades. To date, an analysis of potential spatial influences on clustering of CSA and SAAM cases has not been attempted. To the best of this researcher's knowledge, RAT has not been used as a theoretical lens to analyze clustering of CSA and SAAM. This research addresses this void in the academic literature. The following sections address what is known about sexual victimization perpetrated against minors in the form of CSA and SAAM; explain the fundamental tenets of routine activity theory and discuss its current state in the literature; and describe the development and applicability of spatial and environmental criminology for this particular area of research.

Child Sexual Abuse and Sexual Assault Perpetrated Against Minors

Definition

There is a lack of definitional understanding of the term child sexual abuse (CSA) as it relates to sexual assaults perpetrated against minors (Finkelhor et al., 2014). While it is at least connotatively understood that child sexual abuse is typically a sexual act perpetrated against a minor by an adult (Finkelhor et al., 2014), there is no definitional exactness to suggest that sexual assaults perpetrated against minors are explicitly different from typical CSA cases. In fact, the annual report produced by the U.S. Department of Health and Human Services (2017) does not make mention of perpetrator age as it relates to the minor victim in their official definition of child sexual abuse:

> A type of maltreatment that refers to the involvement of the child in sexual activity to provide sexual gratification or financial benefit to the perpetrator, including contacts for sexual purposes, molestation, statutory rape, prostitution, pornography, exposure, incest, or other sexually exploitative activities (p. 114).

However, it is important to note that some individual state criminal codes, such as Delaware, make the distinction that sexual abuse must occur at the hands of someone who is responsible for the “care, custody and control of the child” (U.S. Department of Health and Human Services, 2017, p. 145). This lends credence to the idea that CSA is generally understood, at least roughly, as sexual acts perpetrated against minors by those who are in some authoritative position, or at the very least, by those who are significantly older than the minor victim (Finkelhor et al., 2014). In fact, many prevalence studies make no distinction between SAAM and instances of CSA by an adult or caregiver.

In a review of the prevalence literature, Finkelhor and colleagues (2014) stated that, “population surveys and meta-analyses using the term ‘sexual abuse’ have generally reported rates that include large numbers of offenses at the hands of same age peer” (p. 330). This is problematic because there may be fundamental differences in the factors influencing a same-aged perpetrator and adult perpetrator to engage in sexual activity with a minor. In this study, CSA will be distinguished from SAAM by the age of the alleged perpetrator. CSA includes cases perpetrated by offenders 18 years or older and SAAM includes cases perpetrated by offenders less than 18 years of age.

<u>Prevalence</u>

When it comes to the official measurement of deviant behavior there are various sources that are typically used. These are the Uniform Crime Reports (UCR), National

Incident-Based Reporting System (NIBRS), and the National Crime Victimization Survey (NCVS). However, when it comes to capturing the prevalence of incidents of child sexual abuse and sexual assaults perpetrated against minors, there are fundamental flaws with using these sources of data. Both the UCR and NIBRS rely on reporting incidents to police before they can be aggregated and estimated for prevalence. The UCR is a frequently used source of official statistics in criminological research. Unfortunately, the UCR does little to capture sexual crime. The UCR does report rape, but does not distinguish between child victims and adult victims. This makes police statistics on CSA and SAAM prevalence impossible to estimate when only relying on rape cases. Fortunately with the increased proliferation of reporting to NIBRS, more detailed reports are possible for law enforcement interaction with CSA and SAAM cases. NIBRS reports identify and report on cases of sexual violence perpetrated against minors where the UCR only reports rape broadly (Finkelhor & Ormrod, 2001).

In a review of NIBRS, Finkelhor and Ormrod (2001) observed that 23% of all reported child abuse cases constituted CSA. They also found distinct rates of reporting based on offender type. Nineteen percent of all reported child abuse cases were committed by a parent or guardian and 63% of reported cases were perpetrated by a non-caretaker acquaintance. Finkelhor and Ormrod (2001) compared the data with welfare reports and found that the rates were somewhat comparable; in the studied sample, NIBRS data actually had higher rates of reported CSA. An important distinction was that welfare organizations responded to higher proportions of cases with younger children, and law enforcement agencies responded to cases with older children (Finkelhor & Ormrod, 2001).

Little is known about the dark figure between true prevalence and reported rates of prevalence to law enforcement, but data suggest that a significant number of CSA cases are not reported to law enforcement agencies (Finkelhor & Ormrod, 2001). This problem persists with regards to sexual victimization generally, independent of the age of the victim (Daigle & Muftic, 2015). The NCVS is fundamentally different from both UCR and NIBRS systems as the NCVS relies on victim self-reports of victimization rather than cases reported to law enforcement. Thus, the NCVS includes crimes not reported to law enforcement. The challenge with using the NCVS reporting statistics to estimate prevalence of CSA and SAAM cases is that they only survey individuals 12 years and older. Additionally, the NCVS is a household survey. Considering the sensitive nature of CSA and that perpetrators are often within the home, or close associates, it is unlikely that these cases would be reported accurately on the NCVS. The advantage with NCVS data, however, is that rape and sexual assaults are reported separately. According to a special report of the NCVS, minor girls aged 12-17 years experienced a rape and sexual assault rate of 11.3 per 1,000 between the years 1994-1998, 7.6 between the years 1999-2004, and 4.1 between the years 2005-2010 (Planty, Langton, Krebs, Berzofsky, & Smiley-Mcdonald, 2016).

Some official prevalence estimates come from incidents reported to child service agencies. However, these apply exclusively to CSA and do not address potential SAAM cases. In a press release from 2002, the U.S. Department of Health and Human Services reported that CSA cases were approximately 10% of all official child abuse cases in 1992 (Putnam, 2003). The official report, *Child Maltreatment from the U.S. Department of Health and Human Services* (2017) noted that 8.6% of all reported maltreatment cases are

CSA; again, this does not include potential SAAM cases. These estimates are much lower than those established by other researchers outside of non-official sources. But again, it is important to note that almost none of these address the prevalence of SAAM.

Finkelhor's (1979, 1984) work was a noteworthy attempt to determine the prevalence of CSA. His early findings were that girls were much more likely to be victims; the median age of abuse was 8-12 years of age; and approximately 20% of both middle and low class families experienced CSA. In a review of 16 cross-sectional surveys between 1965 and 1997, Gorey and Leslie (1997) measured CSA in 14.5%-22.3% of girls and 7.2%-8.5% of boys. An international study found similar proportions of 19.7% for women and 7.9% for men (Pereda et al., 2009). A more recent prevalence estimate included both CSA and SAAM cases, and measured self-reported prevalence for minors aged 15, 16, or 17 years of age (Finkelhor et al., 2014). The percentages increased each year from 15 to 17 years of age. Finkelhor and colleagues (2014) argue that the most accurate prevalence estimate would be that of the 17 year olds as the survey asked if they had experienced SAAM or CSA at any point in their lives. The identified estimates were 26.6% for girls and 5.1% for boys. For CSA cases specifically, these were 11.2% for girls and 1.9% for boys. For SAAM cases, the rates were 17.8% for girls and 3.1% for boys (Finkelhor et al., 2014). These proportions are much higher than official reports, but fall within the majority of prevalence estimates (see Finkelhor 1979, 1984; Gorey & Leslie, 1997) from other reports concluding that the general CSA/SAAM prevalence is likely somewhere around 1 in 4 for girls and 1 in 20 for boys (Finkelhor et al., 2014).

<u>Predicting Factors</u>

CSA cases and SAAM cases are inherently different in what motivates offenders and how victims are selected. There are several theoretical explanations which seek to explain why adults may be motivated to offend against children, and a separate body of literature addresses the motivations for sexual assault generally. In his analysis of CSA, Finkelhor (1984) identified certain demographic variables that contributed to the likelihood of CSA. In his sample, gender and age influenced risk dramatically. Most victims of CSA were girls, aged 8-12 (Finkelhor 1984; Finkelhor & Baron, 1986). Early studies found a complicated relationship between socioeconomic status and risk for CSA (Finkelhor, 1984; Miller, 1976; Russell, 1983). Poorer and middle-class families had comparable victimization rates, but they were significantly higher than wealthier families (Finkelhor, 1984). Race and ethnicity have little reported effect on the likelihood of CSA (Finkelhor & Baron, 1986; Kercher & McShane, 1984; Russell, 1983).

Finkelhor (1984) identified familial risk factors that contributed to the likelihood of CSA: families with step-parents, families with non-biological mothers, and emotionally disconnected mothers. Adult men and women who reported living for a time without one of their parents and growing up in unhappy home environments were more likely to have been victims of CSA (Finkelhor, Hotaling, Lewis, & Smith, 1990). In a study of 1,000 18 year old New Zealand youth, familial instability and poor parent-child relationships increased the likelihood of CSA victimization (Fergusson, Horwood, & Lynskey, 1996). There is generally a lack of research into specific risk characteristics for victims of CSA, but the consensus that does exist is that young girls from poorer and single-parent family units are most at risk for victimization (Fergusson et al., 1996; Finkelhor, 1984; Finkelhor et al., 1990).

There is little research identifying predictive factors for sexual assault (SA) victimization, specifically perpetrated against minors, but the literature for sexual assault generally helps inform this inquiry. The majority of research in this area, as with CSA, focuses on female victims. This is to be expected considering the high rates of female victimization in cases of sexual assault (Daigle & Muftic, 2015). In cases of SA, there are static risk factors and dynamic risk factors for victimization. Static risk factors have less to do with the lifestyle decisions of potential victims and more to do with concrete characteristics like race, socioeconomic status, and age. Dynamic risk factors are more likely to have to do with lifestyle choices like alcohol consumption and social life. For the purpose of a spatial analysis of CSA and SAAM, dynamic risk factors would be difficult to measure at the community level and will not be included in this analysis. Unlike CSA, SA cases are more influenced by race and ethnicity. Native Americans and African Americans are more at risk for rape and attempted rape victimization (Lodico, Gruber, & DiClemente, 1996; Söchting, Fairbrother, & Koch, 2004; Russell, 1983). Victims of SA are also at an increased risk for repeat victimization in adulthood, even if the initial victimization occurred in childhood years (Gidycz, Coble, Latham, & Layman, 1993; Maker, Kemmelmeier, & Peterson, 2001; Messman & Long, 1996; Söchting et al., 2004). Besides these more established risk factors for SA, poverty and other familial characteristics may play a predictive function in cases of SAAM and CSA.

Children coming from single-parent families are at higher risk for SAAM (DeFrancis, 1971). In a summary of the general findings of DeFrancis's (1971) work, Gruber and Jones (1983) said, “A large number of child sex victims came from homes characterized by parents with personal and social problems such as alcoholism, physical or mental handicaps, mental retardation, insufficient education, or illiteracy” (p. 18). The relationship between poverty and alcoholism is complicated (Jones & Sumnall, 2016; Seccombe, 2000). Though there may be societal differences, a recent Dutch study found evidence to suggest that individuals from low-income environments refrain from consuming alcohol (Kuipers, Jongeneel-Grimen, Droomers, Wingen, Stronks, & Kunst, 2013). However, others have found that they may drink alcohol excessively (Matheson, White, Moineddin, Dunn, & Glazier, 2012). Poverty may also increase the likelihood of child abuse generally (Bywaters, Bunting, Davidson, Hanratty, Mason, McCartan, & Steils, 2016; Seccombe, 2000), suggesting the possibility of a relationship between poverty and CSA. In a massive meta-analytical study published in the United Kingdom, children from lower-income families were significantly more likely to experience child abuse and neglect, including sexual abuse (Bywaters et al., 2016). Families below the poverty line are more likely to be headed by a single parent (Seccombe, 2000). Parents are more likely to be authoritarian and punitive in poorer families, and the parent-child relationships in low-income families are much weaker (Magnuson & Duncan, 2002). Single-parent families and families in which the parents did not have a strong marital relationship were good predictors of risk for SAAM in a small sample of female youth (Gruber & Jones, 1983). In a multivariate analysis of their data, the combination of poor parental relationship, single parent families, and poor relationship with the mother was a significant risk factor for SAAM (Gruber & Jones, 1983).

A reductionist viewpoint of this argument could be misconstrued as the idea that poorer and single-parents are bad parents, but this is not the claim here. The concept underlying this analysis is a well-documented and well-supported family stress model (Chaudry & Wimer, 2016; Conger, Ge, Elder, Lorenz, & Simons, 1994). This is the idea that lack of income in a family setting can strain the parents to the point of not being able to provide adequate rearing in a way that can stress the parent-child relationship (Chaudry & Wimer, 2016). This is not to say that all low-income families result in poor child development, only that it is harder for parents and children to bond in these financially strained settings. Citing three earlier studies testing the strength of parent-child relationships, Chaudry and Wimer (2016) said, “across childhood, low family income has been linked to many relational qualities between parents and their children, including less secure attachment, less warmth, less attention, harsh discipline, and negative mood” (p. S26). In a study of 118 mothers, adverse childhood experiences were significantly more prominent in mothers of low-income families (Steele, Bate, Steele, Dube, Danskin, Knafo, & Murphy, A. 2016). It is important to note that this study included only 33 mothers in the low-income category, which could skew the results.

In general, the correlation between financial stress and the likelihood of child maltreatment indicates a connection. It is well documented that poorly developed or weak parent-child relationships are a strong predictive indicator of the likelihood of CSA and SAAM (DeFrancis, 1971; Fergusson, et al., 1996; Finkelhor, 1984; Finkelhor et al., 1990; Gruber & Jones, 1983). Furthermore, levels of low-income have been seen to greatly affect these parent-child relationships in a damaging way (Bywaters et al., 2016; Chaudry & Wimer, 2016; Steele et al., 2016). The evidence suggests that parents who are financially strained either by poor economic status or the restraint of single-parenthood may have a more difficult time positioning themselves as adequate protective guardians against potential victimization for their children. Finkelhor (1984) best demonstrated this in his interpretation of the data regarding poor mother-daughter relationships. There seems to be some undeveloped protective status for parents who have difficulty bonding appropriately with their children.

The Routine Activity Perspective

Routine activity theory (Cohen & Felson, 1979; Cohen, Felson & Land, 1980; Cohen & Cantor, 1980) is a staple theory in the field of criminology. The theory hinges on three distinct elements, each requisite for the occurrence of a criminal incident. These elements, as originally identified by Cohen and Felson (1979), are: a motivated offender, a suitable target, and lack of guardianship. According to the theory, all three elements converge in space and time for a criminal event to occur (Cohen & Felson, 1979). Eck and Weisburd (1995) later suggested the addition of place as a necessary element of crime, expanding the original three elements to four. This is an essential addition because it adds credence to the influence that place may have beyond a mere convergence of characters. Eck and Weisburd's (1995) addition of place begs the question, do characteristics of place increase the likelihood of victim and offender convergence in space? Jensen and Brownfield (1986) masterfully distil the complex theory in this statement, "the greater the accessibility of targets and the less targets are protected, the greater the opportunity for crime" (p. 86). At its core, RAT shifts focus from the epidemiological investigation of motivations for offenders toward the interaction of victims and offenders in a physical space. Criminal motivation is a phenomenon that theory has attempted to explain since the inception of criminological inquiry. However, the original intent of Cohen and Felson's (1979) work was not to understand motivation, but to understand how the environmental circumstances of each criminal event might be affected by the characteristics of potential targets or victims.

RAT has been well received in the criminological field. This is evidenced by a vast body of replicated studies, each seeking to test the applicability of the theory as an explanation for a specific subset of crime or deviant behavior. Although the initial intent of Cohen and Felson's (1979) work was to explain an increase in cases of street crime, researchers quickly recognized its utility in a variety of criminal contexts. Soon after the initial publication (Cohen & Felson, 1979), other researchers joined in on the emergent perspective. Jensen and Brownfield (1986) used RAT as a theoretical lens through which they analyzed a range of adolescent victimization experiences. Others also recognized the benefit of seeing crime through this environmental perspective. Sampson and Wooldredge (1987) found that the frequency at which young people went out at night significantly increased their likelihood of victimization. They determined that certain geographic contextual factors increased the likelihood of certain types of crime. Community-level characteristics of single-headed households, population density, unemployment, and family disruption increased the likelihood of burglary independent of individual characteristics (Sampson & Wooldredge, 1987). Even in its infancy, the environmental utility of RAT was beginning to take shape.

One of the fathers of the hotspots perspective of crime, an area which will be further explored, cemented himself in the RAT literature as well (Sherman, et al., 1989). Sherman and colleagues (1989) pushed the individual and community-level RAT theory into the spatial field in their analysis of 329,979 calls for service in Minneapolis. In their sample, an overwhelmingly disproportionate number of criminal events occurred in a very small set of physical locations. In the sex crime context, they found that reported rapes occurred in only 1.2% of all possible locations. This work strengthened the body of support for the RAT perspective and added a new level of intricacy to the model. Not only did crime result from the convergence of motivated offenders and suitable targets lacking guardianship, but these convergences were much more likely to occur in specified, non-random locations much as Eck and Weisburd (1995) later explained. These concepts would spur the next generation of environmental criminology on the back of Brantingham and Brantingham's (1993) crime pattern theory. Crime pattern theory is a deeper analysis of the non-random selection of physical space for criminal behavior. Offenders are much more likely to offend in areas with which they have familiarity. While this seems obvious, the concept of offenders' activity area helps explain the non-random distribution of crime in certain places at certain times.

The applicability of RAT as an explanation for violent victimization has been one of great interest to researchers since the inception of the original theoretical perspective. In their initial publication, Cohen and Felson (1979) analyzed several violent crime categories including aggravated assault and rape and found that regular activities that brought people out of their homes and in contact with others increased the likelihood of victimization. In a qualitative analysis of a group of delinquent street youth, Kennedy and Baron (1993) found that RAT alone was not sufficient to explain incidences of violent victimization. They argue that subcultural influences greatly impact the choice of victim and type of violence. Along a similar line, Miethe, Stafford, and Long (1987) argued that

RAT was likely not the best explanatory theory for instances of violent victimization. However, Kennedy and Forde (1990) disagreed; they argued that the findings from Miethe et al. (1987) were due to a poor data source. Using richer data from the *Canadian Urban Victimization Survey*, they found that the individuals in their sample were more at risk for victimization if they led lives that increased their public interactions. This was particularly true for certain demographic groups like young males (Kennedy & Forde, 1990). In a more recent inquiry, the RAT perspective predicted violent victimization across age and gender with some small mediating effects (Henson, Wilcox, Reyns, & Cullen, 2010). RAT is also an applicable analytical tool in instances of physical peer victimization (Cho, Hong, Espelage, & Choi, 2017). Although the classic RAT theory (Cohen & Felson, 1979) included an analysis of rape, the general social understanding of sexual victimization has evolved to include a myriad of other types of sexual offenses. Subsequently, some researchers have begun to extend the principles of RAT to sexual victimization as well.

In the examination of sexual victimization, a common population of study is undergraduate college students. This is likely because students experience high levels of sexual victimization (Daigle & Muftic, 2015) and because undergraduate students are easily accessible to researchers. An early analysis of this nature concluded that women were perceived to be suitable targets by sexual predators on campus if they frequently went out drinking and if they were more closely associated with men who encouraged female drinking (Schwartz & Pitts, 1995). Schwartz, DeKeseredy, Tait, and Alvi (2001) later developed this perspective to explain male motivation for sexual assaults perpetrated against women on campus. Certain routine activities, such as number of days during the week women spent on campus and how much they "partied" were associated with increased rates of sexual victimization (Franklin, Franklin, Nobles, & Kercher, 2012). Each of these studies analyzed individual-level routines as predictive measures of sexual victimization on campus, but school-level routine activities have also been studied to see if macro-level school characteristics are predictive. Cass (2007) concluded that individual routine activities were much more effective at predicting sexual victimization and surprisingly that school-level routines and efforts to curb victimization had little effect. These studies represent a necessary extrapolation of RAT to sexual victimization. Tewksbury and Mustaine (2001) found RAT had predictive utility in their study of the sexual assault of male victims. Drug use, alcohol use, and high school experiences increased the likelihood of sexual victimization (Tewksbury & Mustaine, 2001). A growing body of literature has addressed the applicability of RAT to a variety of criminal activities like cybercrime, property victimization, violent victimization, and even some sexual assault. However, there is an apparent gap in the analysis as it pertains to instances of child sexual abuse or sexual assault perpetrated against minors.

It is somewhat surprising that there are almost no studies of CSA through an RAT lens considering early recognition of its theoretical utility (Mannon, 1997). While researchers were rapidly affixing RAT to several types of victimization, James Mannon (1997) published a theoretical analysis of the potential effectiveness RAT might have as an explanation of CSA and the sexual assault of minors. He argued that perhaps CSA was not originally conceived as a potential avenue for RAT because, at the time of its inception, incidents of CSA were believed to be extremely rare. RAT focused primarily on the mundane or routine types of victimization thus negating the apparent applicability to the rare case of CSA. However, he argued, in the wake of new evidence suggesting that CSA was much more prevalent than previously anticipated (Finkelhor, 1984; Gruber & Jones, 1983; Summit & Kryso, 1978), RAT was ripe for application. Mannon (1997) expertly recognized the potential effects that family environment had on potential sexual victimization. Others have similarly recognized the family context in this way, but with regards to peer victimization (Schreck & Fisher, 2004). Where CSA makes an interesting contribution to the RAT perspective is in the interconnectedness of guardians, offenders and suitable targets. In cases of CSA, offenders themselves are often those that society would expect to operate as capable guardians (Finkelhor, 1984: Russell, 1983). Similarly, what makes victims suitable in these instances is often the lack of guardianship itself (Mannon, 1997). These unique intricacies of CSA characteristics make it ripe for analysis through an RAT lens. The current study aims to empirically test what Mannon's (1997) theoretical foundations as they pertain to the sexual victimization of children and the applicability of routine activity theory.

Hotspots, Clustering, and Environmental Criminology

The idea that places, and not people, might be criminogenic was revolutionary in the criminological literature. This new perspective can be traced back to the early works of Shaw and McKay (1942). Shaw and McKay (1942) analyzed the patterns of growth in an urban environment and argued that crime and deviant behavior were more likely to occur in what they called the zone of transition. The zone of transition was the area of an urban city with higher rates of poor immigrants and residential mobility. They argued that this area was more criminogenic because these social factors created a state of disorganization (Shaw & McKay, 1942). Shaw and McKay (1942) argued that crime was more likely to occur in a large area of the urban environment, however, later research demonstrated that there were specific places within those disorganized neighborhoods that were particularly criminogenic (Sherman et al., 1989). Using the cutting-edge software of the day, Sherman and colleagues (1989) plotted all Minneapolis calls for service and found that a disproportionate number of crimes occurred in a small number of places. Specifically, all thefts occurred in 2.7% of places, robberies in 2.2%, and rapes in 1.2% of places (Sherman et al., 1989). The idea that crime could cluster in small areas within neighborhoods spurred a new line of research and policing strategies called hotspots.

Hotspots

In their well-known experiment, Sherman and Weisburd (1995) identified hotspots of crime and randomly assigned increased numbers of police patrol to measure the effect of police presence on crime hotspots. Hotspots were defined as small geographic areas in a city in which crimes cluster, or are more likely to occur (Sherman et al., 1989; Sherman & Weisburd, 1995). The experiment spurred continued replication in similar studies and further strengthened the idea that places were criminogenic. There were early concerns that these targeted intervention strategies might displace the occurrence of crime to other non-targeted locations, which was referred to as crime displacement (Barr & Pease, 1990; Eck, 1993; Hesseling, 1994). Hesseling (1994) identified five different forms of displacement in spatial, temporal, target, tactical, and crime-type. Others have argued that the inverse may also have an effect or that the crime-reduction benefits of targeted intervention strategies may diffuse to non-targeted areas (Guerette & Bowers, 2009). The measurement of displacement and diffusion has evolved over the years but the findings consistently demonstrate a relatively equal balance between possible displacement and diffusion (Braga, Papachristos, & Hureau, 2014; Guerette & Bowers, 2009; Johnson, Guerette, & Bowers, 2014).

Hotspots were later identified in cases of open air drug markets (Weisburd & Green, 1995). Together with local business owners and public initiatives, increased police patrol presence in targeted drug market areas resulted in a significant reduction in disorder-related crimes with little evidence of crime displacement (Weisburd & Green, 1995). Hotspots exist for gun-related crimes as well (Sherman & Rogan, 1995). Targeting specific hotspot areas, increased enforcement of gun laws and increased patrol presence reduced gun-related crimes 49% in the target areas, again with little evidence of displacement (Sherman & Rogan, 1995). It appears that researchers latched onto the idea of hotspots, not only as an effective tool for appropriating limited police resources, but also as a method of measuring crime clusters for specific subsets of crime types.

Continuing in this trend, hotspots have been identified in cases of robbery and assault in New Jersey (Braga et al., 1999). Street-level violent crime hotspots were paired with non-hotspot areas and targeted for police intervention strategies. The results were similar to those past; significant reductions in targeted crime with little evidence of displacement (Braga et al., 1999). Similar findings have since been replicated in more recent studies (Ratcliffe, Taniguchi, Groff, & Wood, 2011). Hotspots were identified for homicide, aggravated assault, and outdoor robberies (Ratcliffe et al., 2011). Just as before, significant reductions in these violent crimes were observed in targeted areas (Ratcliffe et al., 2011). Hotspots analyses repeatedly supply strong evidence to suggest the effectiveness of increased police presence in high-crime places. However, this is not the extent of the utility of hotspot analysis. The studies mentioned to this point have only identified hotspots and targeted them with specific crime-reduction strategies to reduce occurrences (Braga et al., 1999; Ratcliffe et al., 2011; Sherman et al., 1989; Sherman & Rogan, 1995; Sherman & Weisburd, 1995; Weisburd & Green, 1995), but few make comprehensive attempts to understand the reasons crimes cluster the way they do.

Crime Mapping

The measurement of hotspots has advanced significantly in recent years (Braga et al., 2014; Chainey et al., 2008). Point mapping was one of the earliest methods. Researchers simply marked a spot on a map where an incident occurred and looked for apparent clustering (Chainey et al., 2008). With the advent of computers and new spatial software came clustering analyses that were both more complex and more accurate. Using an early program called Spatial and Temporal Analysis of Crime (Illinois Criminal Justice Information Authority, 1996), spatial ellipses measured the statistical likelihood that an event would occur in areas around identified clusters. These clusters were calculated from measured incidents one or two standard deviations from the mean center of each cluster (Chainey et al., 2008). Thematic mapping was another relatively rudimentary way of measuring hotspot clustering. Thematic mapping measures incidents that occur in selected geographic units and color-codes the units based on the density of incidents in each unit. The units of measure could be police beats, census units, cities, counties, states, or even regions. Although simple to conduct and interpret (Chainey et al., 2008), this method lacks accuracy due to arbitrary divisions and changing boundaries (Chainey & Ratcliffe, 2005; Eck, Chainey, Cameron, Leitner, & Wilson, 2005; Openshaw, 1984). Grid mapping is similar but overcomes the challenges of arbitrary boundaries by overlaying a grid across the measured space (Chainey et al., 2008). This method is slightly better than thematic mapping, but is visually unattractive and variable grid units make generalizability an issue (Chainey et al., 2008; Eck et al., 2005).

One of the most visually appealing and accurate method to date is kernel density interpolation models, sometimes referred to as kernel density estimations (Chainey et al., 2008, Eck et al., 2005; Levine, 2002, 2006). Kernel interpolations take grid mapping one level deeper. A grid overlay is used to assign density scores to each grid unit. Then, scores are calculated for each grid unit which includes density scores of nearby grid units as well. These scores are then used to create a smooth image of clustering that is generally represented visually with a heat map color-scheme (Chainey et al., 2008; Hill & Paynich, 2013; Levine, 2002, 2006). In a comparison of hotspot measuring methods, kernel interpolation was found to be the most accurate, and the best method for predicting future incidents of crime (Chainey et al., 2008). It is one thing to recognize that specific types of crime cluster in small areas, but it is another thing entirely to understand what factors influence that clustering.

Environmental Criminology

Shaw and McKay (1942) hypothesized that social disorganization factors were the underlying causal factors of crime clustering, at least in the zone of transition. They identified environmental factors that resulted in crime clustering such as ethnic heterogeneity, increased rates of poverty, and residential mobility. These factors, they argued, encouraged crime to flourish in more disorganized areas of the urban environment (Shaw & McKay, 1942). Sampson (1987) later expanded social disorganization to include family disruption as an environmental factor before empirically testing the tenets of social disorganization (Sampson & Groves, 1989). The testing of social disorganization is an early explanation of spatial clustering, suggesting that there are underlying environmental and social factors that result in criminogenic places. Other researchers have attempted to explain why crimes cluster in hotspots. One popular explanation was that of crime pattern theory (Brantingham & Brantingham, 1993), which has previously been mentioned. Although social disorganization theory (Shaw & McKay, 1942) and crime pattern theory (Brantingham & Brantingham, 1993) are drastically different, they are each explanations of the factors that may result in crime clustering in certain spaces. Each recognize that there is something environmental that works almost invisibly to move crime into specific areas of a city.

These ideas helped others consider the theoretical explanations for why hotspots formed. In a more modern geospatial analysis of violent trauma hotspots in Canada, Walker, Schuurman, and Hameed (2014) said, “using both space and time concurrently to understand urban environmental correlates of injury provides a more granular or higher resolution picture of risk” (p.1). This statement recognizes the utility clustering analyses have in understanding both the environmental correlates of criminal incidents and the victimization risk individuals have in certain places. Hotspots analyses have been demonstratively beneficial to the general understanding of crime clustering and targeted prevention strategies for both street and violent crime. A series of searches into a variety of academic journals and the internet have yielded no literature to date which seeks to include spatial or environmental predictors for CSA and SAAM cases. This is another reason why this particular line of research is beneficial to the field. Not only have no efforts been made to assess the spatial clustering of CSA and SAAM cases, there is little evidence to suggest that researchers into these types of cases have made a serious effort to consider environmental factors.

In addition, hotspots analyses have not been applied to incidents of CSA or SAAM. This begs the question, do incidents of child sexual abuse and sexual assaults perpetrated against minors cluster in certain areas forming hotspots? And if they do, what underlying environmental factors are influencing that clustering? These questions form the basis of the current study described in the next chapter.

CHAPTER THREE: METHODOLOGY

Hypotheses

It has been well documented that crimes occur in a small subset of places (Sherman et al., 1989). Hotspot clusters have been identified for a wide range of crimes (Weisburd & Green, 1995; Sherman & Rogan, 1995; Braga et al., 1999; Ratcliffe et al., 2011). For these reasons it is likely that cases of CSA and SAAM will cluster as well. Although the evidence is somewhat complex, there is some support for the idea that the parent-child relationships in poverty-level families may be stressed (DeFrancis, 1971; Grueber & Jones, 1983; Seccombe, 2000; Chaudry & Wimer, 2016). Because parents are the primary guardians for children, it is hypothesized that children in areas with increased concentrations of single-parent headed families and families of low socio-economic status will be more at risk for sexual victimization. Thus the hypotheses for the present study are:

Hypothesis 1: Reported incidents of child sexual abuse and sexual assault against minors cluster to form hotspots.

Hypothesis 2: Lack of guardianship, as measured in proportion of single-parent families and poverty in census block-level data, will increase the likelihood of hotspots for child sexual abuse and sexual assault against minors.

Data, Variables, and Measures

This research is a cross-sectional analysis of the collected data. Data for this study was collected at two levels: the individual-level and spatial-level. The individual-level data collected for this study were incidents of sexual offenses perpetrated against minors, including both CSA and SAAM cases reported to a local police department. The data was collected from the police department using their local computer software. Each case was tagged initially at the reporting stage with an offense category and responding officers add observed offense tags to the cases. Any offenses that were identified as forcible fondling, rape, sex assault, sex assault with an object, or statutory rape were included in the data. The incidents were reported to the police department during the 24 month period of January 1, 2016 through December 31, 2017. Although the incidents were reported during 2016 and 2017 they did not necessarily occur during those years. Therefore, in order to make a distinction between CSA and SAAM, both the ages of the victims and the suspects were calculated using the difference in years between the date of the incident, not report date, and the birthdates of the parties. If the age of the alleged perpetrator was at least 18 years old, the case were classified as CSA and if the alleged perpetrator was younger than 18, the cases were classified as SAAM. This falls in line with the typical understanding of the difference, though few research projects make the distinction (Finkelhor & Ormrod, 2001). Only cases which listed a victim under the age of 18 years old when the offense occurred were included. Importantly, each case was tagged with an X, Y latitude and longitude geographic identifying location for the responding location. There were no cases tagged with the location of any police headquarters location. A total of 110 cases met the criteria to be included in the study.

The spatial-level data comes from the 2017 American Community Survey (ACS) 5-year estimates of the U.S. Census Bureau. Complete census data was only available in 2010 and due to the speed of development in the area, ACS estimates were much more representative of the current state of the population at that time. The data was collected for 46 block-groups within the city limits. The independent variables collected at the block-group level were: population estimates, population density, male to female ratio, minor population percentage, minority population percentage, proportion of high school graduates, residential mobility, poverty, and children living in single-parent homes.

Population, male to female ratio, proportion of high school graduates, poverty and children living in single-parent homes were pulled directly from the ACS files. Population density was measured by dividing the number of households by the number of individuals in each block group. Minor population percentage was calculated as the percentage of total population under the age of 18 years old. The minority population was the percentage of non-White residents in each of the block-groups. The residential mobility measure was determined by summing all homes that had been moved into between the years 2010 and 2017 and dividing that by the total number of households in each block group. The poverty and single-parent children measures were added together to create a composite lack of guardianship independent variable measure. The dependent variables for the study varied depending on which type of analytical study was employed. One statistical method was used to test Hypothesis 1, and 2 methods were used to test Hypothesis 2.

Hypothesis 1 Testing

For the first analysis, the dependent variable is hotspot clustering. The formation of hotspots was determined using ArcGis software in collaboration with the CrimeSTAT IV program. ArcGIS automatically tests the spatial pattern for randomness. If events are clustered, as determined by a Moran's I calculation, CrimeSTAT IV will be used to calculate kernel interpolations which will then be displayed as hotspots on the ArcGIS map. These hotspots will be calculated using single-kernel interpolation, sometimes referred to as kernel density estimation (Chainey et al., 2008). Kernel interpolations will be discussed in more detail below but they rely on a custom user-defined grid size and bandwidth. The most informative grid size was 1,750 square feet with a fixed interval.

The independent variable is the reported location of CSA and SAAM cases. These include all reported cases to the law enforcement agency for the years 2016 and 2017 related to the sexual assault or abuse of minor-aged victims. These cases were plotted spatially and a single kernel density interpolation was run through CrimeStat IV to determine hotspot clustering (Hill & Paynich, 2013; Levine 2002, 2006). The process of single kernel interpolation is a sophisticated hotspot analysis which overlays a grid of determined size over a geographic map. Density scores are then calculated measuring the density of events in each grid, but also including events in nearby grids and dividing them by the areas of each grid unit (Hill & Paynich, 2013; Levine, 2002, 2006). This creates a smooth and detailed density estimate representing “hotter” areas on a map. Hotspots are represented on a raster map image with red areas as hotter clusters. This first analysis is vital for two reasons. First, a hotspot analysis of CSA and SAAM cases has not yet been attempted. Second, in order to test the spatial applicability of routine activity theory as an explanation for the occurrence of CSA and SAAM, the formation of hotspots is necessary to run more complex spatial statistical comparisons between geographic census data and the dependent variable of hotspot clusters.

Hypothesis 2 Testing

Dual Kernel Interpolation

The dependent variable for the second data analysis is also hotspot clustering, as measured through ArcGIS and CrimeStat IV kernel interpolation. However, the independent variable of study in this analysis is entirely different. The independent variable of concern in this analysis is a lack of guardianship composite score as measured through the proportion of single-parent families and families below the poverty line in census block group units. Due to the complexity of a true measure of parent-child relationships and effective, protective parental guardianship, this analysis used census-level poverty and single-parent family data as a proxy measure to represent a lack of guardianship. These data serve effectively for two purposes: their ease of access from the Census Bureau and ability to be used in spatial analyses. Census data are more readily matched to coordinate location data of reported incidents. Using census block group level data, the proportion of single-parent families and the number of families below the poverty line was standardized by the population of each census block. These standard rates were then added together to create the proxy lack of guardianship measure. Investigating lack of guardianship spatially through census data is advantageous in various ways. First, it allows for the spatial application of routine activity theory. Second, it allows for more complicated spatial analysis through dual-kernel interpolation which categorizes geographic areas with unique risk scores for victimization. Third, it opens the door for spatially lagged regression to assess spatial dependence in reported incidents of CSA and SAAM.

Dual kernel interpolation is similar to single kernel interpolation in that they use the same processes of grid construction and spatial division to determine spatial clustering of incidents. Dual kernel interpolation is different is in its ability to begin to explain why incidents cluster and its ability to affix risk scores to geographic units of space based on identified clusters (Bailey & Gatrell, 1995; Levine, 2002, 2006). Typically, dual kernel analysis risk scores are standardized against the total population of each unit for personal crimes or the total number of households for burglaries (Levine 2002, 2006), but, in this case, they were standardized first by the lack of guardianship composite score and then by the number of minors living in a unit as reported by the 2017 American Community Survey. This was appropriate because the variable of interest here was crimes committed against minors, therefore a risk score standardized by total population would not have made sense. This analysis aimed to determine both the potential clustering per unit, as well as a standardized risk score based on the number of minor children living in each unit. This can be particularly helpful to direct potential enforcement and prevention strategies to reduce the likelihood of victimization in high risk areas.

Spatial Lag Regression

A spatially lagged regression was conducted as the culminating analysis for this study. Spatial lag regression is an analytical process which affixes a score to each individual incident calculated from the scores of proximal incidences (Ward & Gleditsch, 2018), meaning that incidents which are near other incidents will be weighted higher than incidents occurring in isolation. Higher scores suggest closer proximity to more events. The score calculated from proximal incidents is referred to as the spatial lag, or weight.

Spatial lag is then regressed in the traditional multivariate model to account for the strength of spatial dependence. Spatial variables facilitate the ability to conduct spatially lagged regressions, which represents a more complete relationship between independent and dependent variables (Ward & Gleditsch, 2018).

Spatially lagged regression models are particularly useful in accounting for potential spatial interdependence among geographic occurrences (Ward & Gleditsch, 2018). Traditional regression models assume independence in studied cases, but hotspot clustering suggests potential interdependence incidents. A spatially lagged regression model replaces the dependent variable with a spatial weight variable accounting for risk of incidence based on proximal neighbors. Independent variables are then used to predict the spatial weight (Ward & Gleditsch, 2018). The primary predictive variable of interest was the lack of guardianship composite score. Consistent with other studies of this nature, the other variables measured here were population density, male to female ratio, minor population, minority population, proportion of high school graduates, and residential mobility. These varaibles were measured as described in the previous section.As a result of these analyses, it was anticipated that cases of CSA and SAAM would not have a random distribution across space, but that they would cluster in certain areas of the city. It was also anticipated that areas with higher lack of guardianship composite scores, as measured through census single parent family and poverty rates, would be positively associated with CSA/SAAM clusters. This would suggest that children living in areas where poverty and family structure might be stressing the parent-child relationship are more at risk for sexual victimization. Furthermore, the results of the lagged spatial regression would determine whether there is environmental interdependence.

CHAPTER FOUR: FINDINGS

Descriptive Statistics

Individual-Level Statistics

In order to distinguish cases of CSA and SAAM from all other cases, it was necessary to calculate the age of the victim from the information reported by responding police officers. After cases with necessary victim age information were separated from the rest of the cases, 110 cases remained. Of those remaining cases, 8 (7.3%) were missing necessary information on the suspect or offender which made the determination between CSA and SAAM impossible. In the 102 cases that had the necessary information for both victims and offenders, 75 (68.2%) were classified as CSA, and 27 (24.5%) were SAAM cases. The higher proportion of CSA cases is not surprising, as the victimization of younger individuals by older perpetrators might be seen as more predatory which could result in a higher rate of reporting to police.

Table 1. Victim and Suspect Age Characteristics

	N	Minimum	Maximum	Mean	Std. Deviation
Victim Age	108	6	17	14.69	2.346
Suspect Age	98	11	60	26.16	12.02
Age Difference	98	0	45	11.57	12.303

In the studied sample, the victim age ranged from 6 years old to 17 years old. The mean victim age of the sample was 14.69 years with a standard deviation of 2.346. For the suspects, the ages ranged from 11 to 60 years old. The mean age for the suspects was 26.16 years with a much higher standard deviation of 12.02. Age difference was calculated for all the cases by taking the absolute value of the difference between suspect age and victim age. The age difference variable ranged from 0 to 45 years. The mean age difference was 11.57 years with a standard deviation of 12.303. There were two cases in which the suspect was younger than the victim. This was a rare occurrence and, for both of those incidents, the victim was 17 years old and the suspects were 16 years old. These statistics do, however, change significantly when CSA and SAAM incidents are analyzed independently.

Table 2 displays the same statistics as Table 1 only categorized by the CSA/SAAM distinction. There are important and obvious differences in these categories. The mean suspect age differs by about 15 years with perpetrators of SAAM cases being about 15 years old and the suspects of CSA cases about 30 years old. The age difference between victims and offenders varies greatly between these two categories as well. The average age difference in CSA cases is about 15 years and just about one year difference in cases of SAAM. What is most interesting, however, is that the mean victim age does not really differ between these two different categories. Both victims of CSA and SAAM average at about 14 years old.

Table 2. Age Statistics by Type of Incident

	N		Mean		Std. Deviation	
	CSA	SAAM	CSA	SAAM	CSA	SAAM
Victim Age	73	27	14.59	14.56	2.467	2.309
Suspect Age	72	26	30.03	15.46	11.819	1.334
Age Difference	72	26	15.33	1.15	12.306	1.891

Other variables of interest in many CSA and SAAM studies are victim and suspect gender. Consistent with the previous literature, a large majority of the reported victims were female. Of the 110 sampled cases, 82.7% (91) were females. There were 17.3% (19) males who had been sexually assaulted or abused in the sample. Only 2.7% (3) of the reported cases identified a female suspect. All of the female suspects victimized males. The victims of male offenders in the sample included 83.9% (73) females and 16.1% (14) males.

The city in which these incidents occurred has a high proportion of White residents. According to the 2010, census 86% were White, 23.8% were Hispanic, 1.1% were American Indian or Alaskan Native, and 0.8% were Black. For the study cases, 80% (88) of the victims were White, 12.7% (14) were coded by police as Latino, and 7.3% (8) were listed as “unknown” by the reporting officers. None of the victims were Black. Offender race was slightly more varied. White offenders were reported in 58.2% (64) of the cases, 19.1% (21) of the offenders were Latino, 3.6% (4) were Black, 0.9% (1) was listed as “unknown” by police, and 20 (18.2%) of the cases did not list information on offender race. These statistics are not surprising considering the general racial characteristics of the city. A racial cross-tabulation between victim race variables and suspect race variables is shown below (See Table 3).

Table 3. Victim-Offender Racial Interaction

		Suspect Race					
		White	Latino	Black	Unknown	Missing	Total
Victim Race	White	51	18	4	0	15	88
	Latino	8	2	0	1	3	14
	Unknown	5	1	0	0	2	8
	Total	64	21	4	1	20	110

The incidents involving White suspects accounted for 79.69% (51) White victims, 12.5% (8) Latino victims, and 7.81% (5) victims listed as unknown. Latino suspects victimized 85.71% (18) White victims, 9.5% (2) Latino victims, and 4.76% (1) victims listed as unknown. All of the Black offenders victimized White victims.

<u>Spatial-Level Statistics</u>

The intention of this research was to study geographic data at the census block-level because these smaller units are much more accurate than larger census tracts. However, due to the smaller size of the city, the census information was unavailable at the block level. In fact, the desired data was only available at the census tract level for the full Decennial Census. In order to study smaller units than the census tracts, 5-year estimates from the American Community Survey (ACS) were collected at the block-group level. Block groups are smaller units than census tracts but larger than blocks (U.S. Census Bureau, 2010). A total number of 110 incidents were plotted on the city map using longitude and latitude coordinate data from the police incident reports. There was one block group with 11 occurrences of CSA/SAAM. Three other block groups had eight occurrences, two block groups had six occurrences, and 32 block groups (38.1%) had between one and four CSA/SAAM incidents during the two-year period. This means that

47 (42.72%) of the incidents occurred in only six of all the 46 total block groups, demonstrating superficial evidence of clustering (See Figure 1).

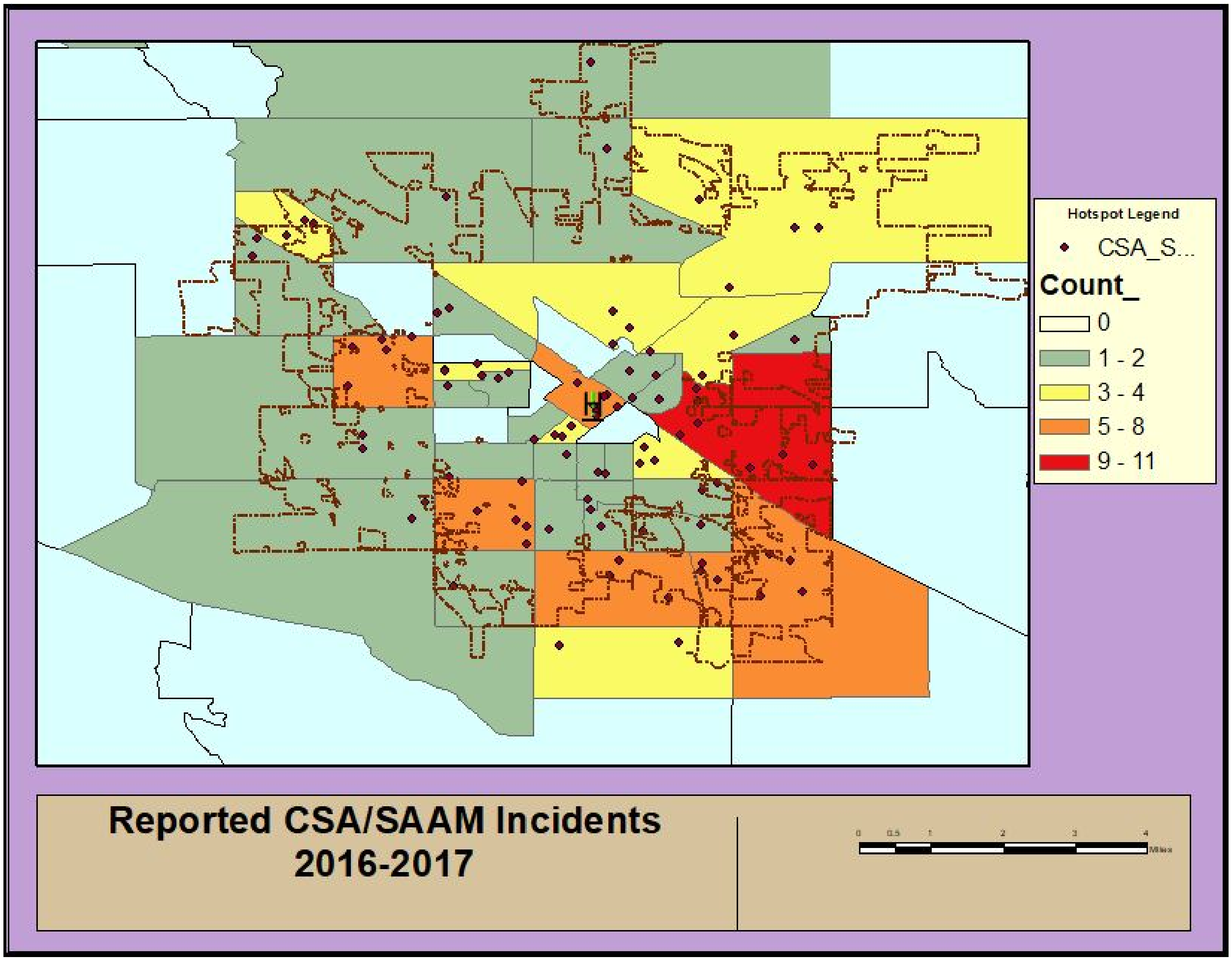

Figure 1. Reported Incidents of CSA and SAAM Choropleth Map

The independent guardianship variable was calculated using 2017 ACS data. Measures of individuals below the poverty line and children living in the home with one parent were divided by the total number of the ACS sample estimates to obtain proportions per block group. These proportions were then added together to create the lack of guardianship composite score in each block group area. The lack of guardianship scores are displayed visually on the map in Figure 2 with basic descriptive information displayed in Table 4. It appears that the central area of the city had higher proportions of poverty and children living with single parents. There was also one isolated block group on the east side of the city that had a high composite score. The highest composite score within the city limits was 0.794. This was the lower half of the vertical rectangle in the center of the city. The second highest score was 0.72 and this is the block group that was the top half of the same rectangle. These findings appear consistent with what would be expected from social disorganization predictions relating to the zone of transition (Shaw & McKay, 1942).

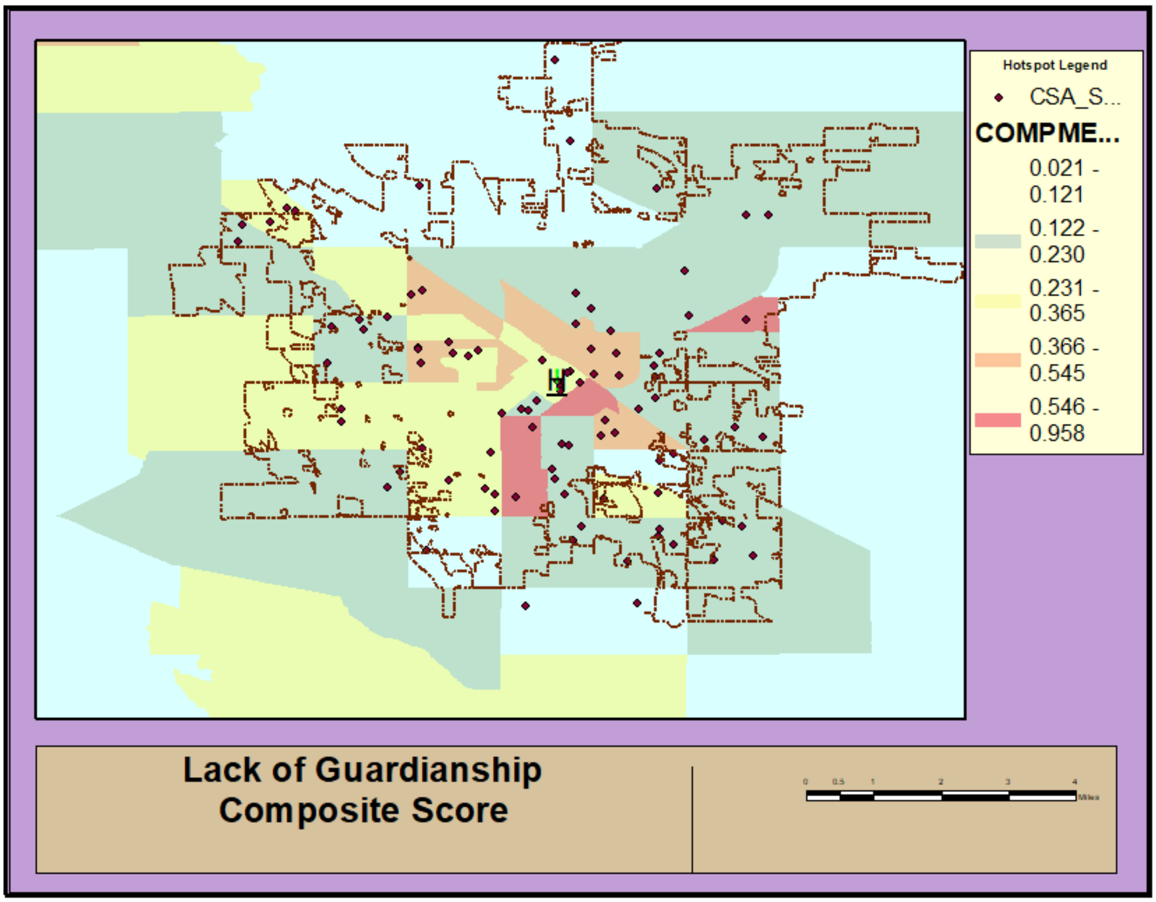

Figure 2. Lack of Guardianship Composite Score per Block Group

Table 4. Lack of Guardianship Composite Score Descriptive Statistics

	Minimum	Maximum	Range	Mean	Std. Deviation
Lack of Guardianship Composite Score	0.021	0.794	0.77	0.28	0.18

Spatial Analyses

Moran's I

From simple observation, it appears that there was evidence of clustering. These incidents did not occur randomly across the city. In order to statistically test for clustering, a Moran's I calculation was necessary. Moran's I is a statistical analysis which tests for the likelihood of random occurrence in space, or spatial autocorrelation. If the calculated Z-score is within the region of acceptance, this suggests that the incidents are not clustered. Using ArcGIS software, the incidents were spatially linked to the census block groups and the Moran's I analysis was calculated. This resulted in a Z-score outside the region of acceptance ($Z = 7.18$). This is evidence of clustering of CSA and SAAM cases in the city for 2016 and 2017, thus supporting Hypothesis 1. Evidence of clustering opened the door to further analyses which aim to determine the influences of clustering.

Single Kernel Interpolation

In order to visually represent the clustering of CSA and SAAM incidents to identify clear regions of clustering, a single kernel interpolation was calculated using CrimeSTAT IV software. CrimeSTAT IV is capable of running various spatial analyses in order to identify and display hotspots in ArcGIS. There are various methods of measuring and displaying hotspots graphically and kernel interpolation is a popular method. Kernel interpolations overlay a fishnet across the measured space and assign scores for grids in which incidents occur. Adjacent and nearby grids are then assigned weighted scores depending on proximity to incidents and the information is stored in an output file which can be visually displayed in ArcGIS software. The user can alter some basic settings in kernel interpolations according to the specific type of data and geographic area of measurement. After adjusting various settings, a grid interval of 1,750 square feet with a quartic method was selected for the interpolation because it resulted in the most visually informative display of the interpolated data. Grid intervals set too high can wash out smaller clusters while low intervals inflate the visual representation of clusters on the map. Interpolations allow for fixed intervals, variable intervals, or adaptive intervals. Fixed intervals keep the grid intervals at a constant across the measured space; this setting was also selected for the interpolation. The results of the interpolation are displayed in Figure 3.

"Hotter" areas are displayed in red (or darker in greyscale). Decreased clustering areas are displayed in orange, yellow, and green. It is easy to see the clustering of these incidents when interpolation is visually represented on the map. This particular city is densely populated in the center of the city and the population density decreases as you move away from that center. It is clear that CSA and SAAM incidents tend to cluster closer to the downtown, dense area of the city. Although this map demonstrates further support of the first hypothesis, this is not the complete extent of the analytical power of single kernel interpolation.

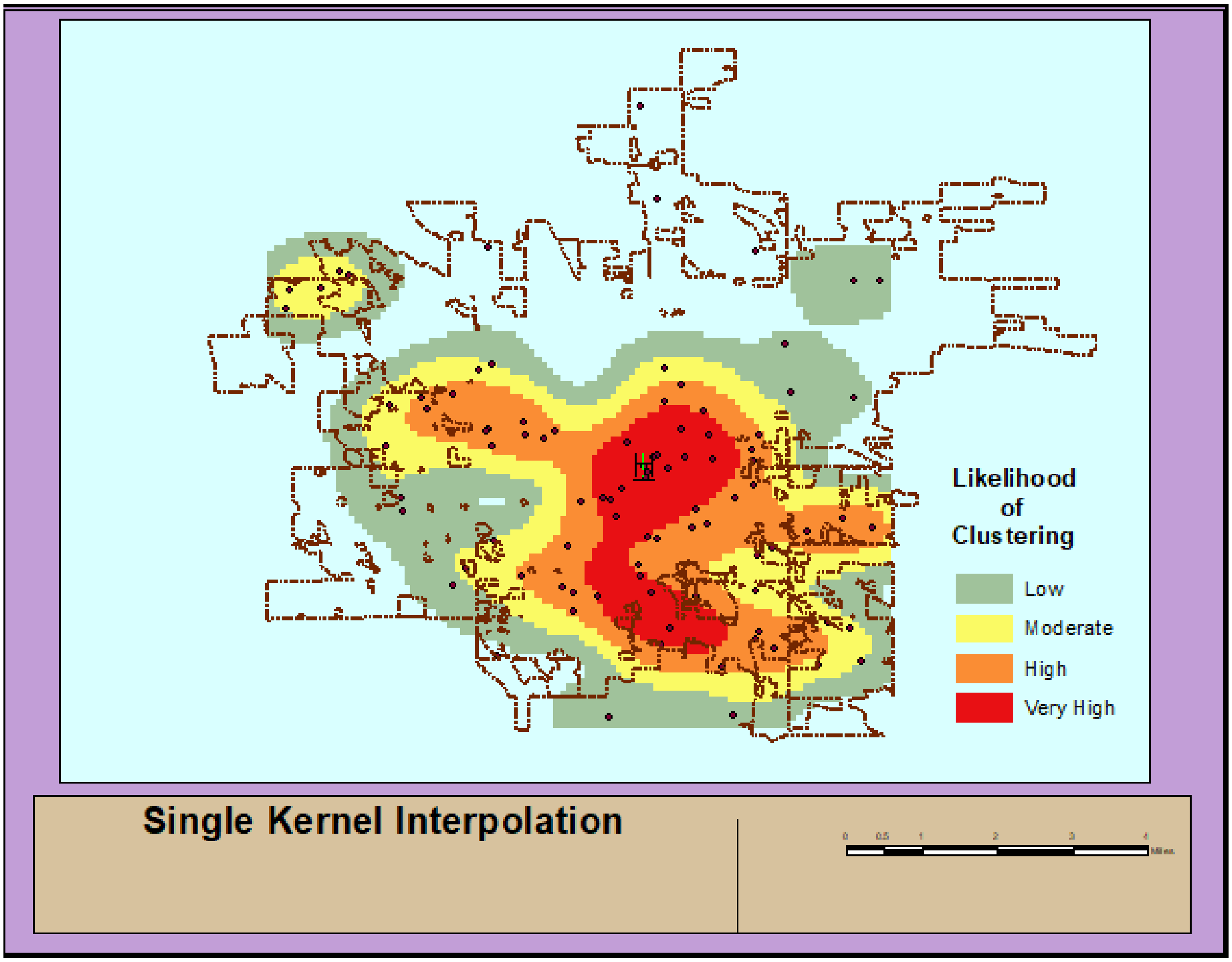

Figure 3. Single Kernel Interpolation

One helpful feature is to add a weighting variable. Weighting variables account for fluctuations in geographic space for variables that may be affecting the overall clustering of the events (Levine, 2006). Typically, kernel interpolations are weighted against the population of geographic units to account for variability in population density. Crimes are often more likely to occur in areas with more people; however, in this instance, we are concerned with crimes that affect minors only. Therefore, the kernel interpolation was weighted by the ratio of population under the age of 18 in each block group. The results are displayed in Figure 4.

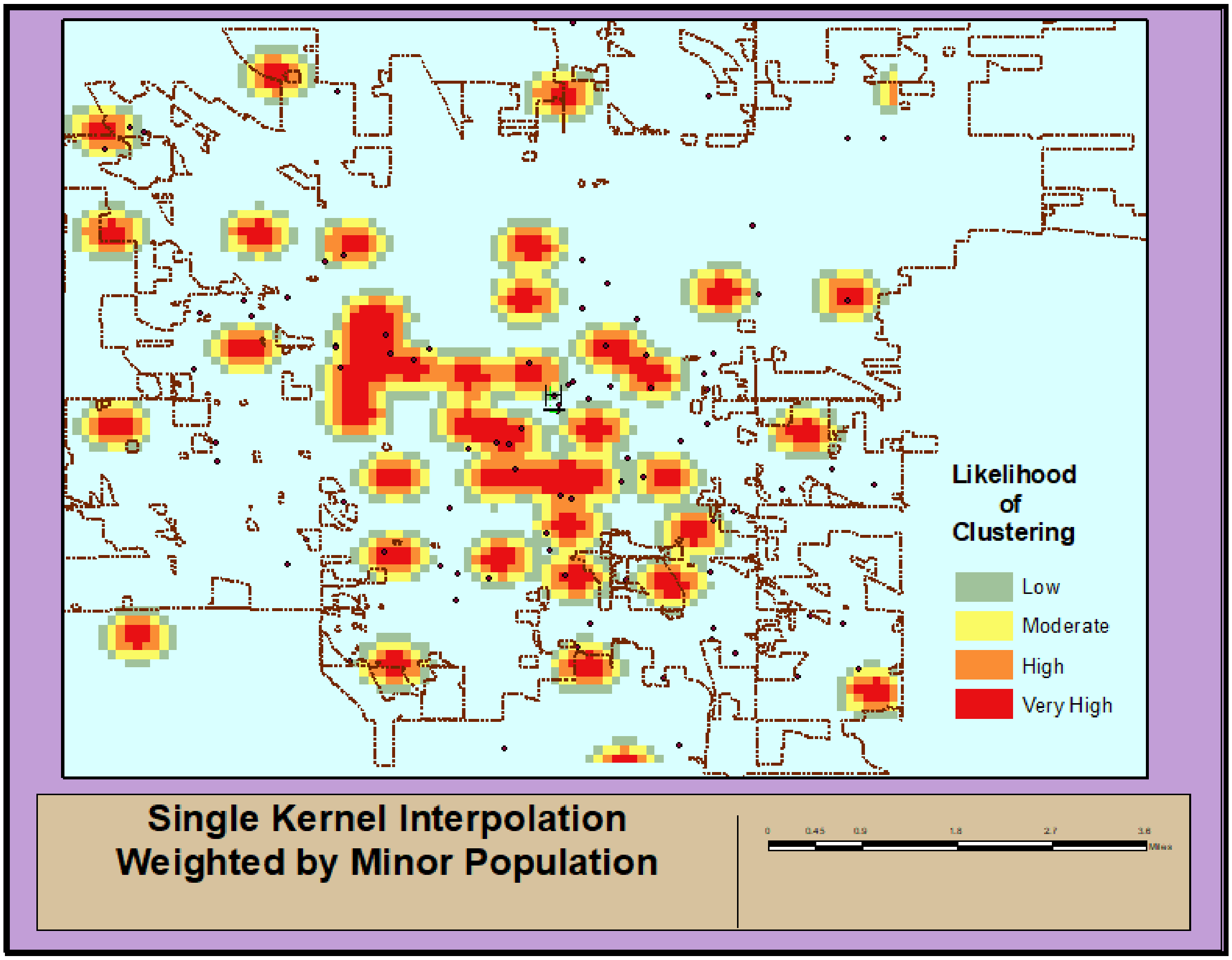

Figure 4. **Single Kernel Interpolation Weighted by Minor Population**

The hotspots identified by the weighted interpolation are much smaller and precise. This particular analysis accounts for both the clustering of CSA and SAAM incidents as well as the number of potential victims in each block group area. Due to the abnormal shape of block group boundaries, many incidents fall outside of areas that show evidence of clustering in this weighted model. However, there is still a strong group of clusters in the central area of the city, further demonstrating that clustering exists there even when accounting for the population of potential victims in those areas. Again, this supports Hypothesis 1 that CSA and SAAM incidents do cluster in geographic space. In order to test Hypothesis 2, however, it is necessary to measure the relationship between lack of guardianship and the clustering of incidents. In order to do that with more than one variable a dual kernel interpolation method was used.

Dual Kernel Interpolation

Dual kernel interpolations are calculated by taking the single kernel score and standardizing it over the interpolation of the second variable. The second variable in most dual kernel interpolations is a population or household count. It is popular to standardize clustering by population totals. Dual kernel analyses are particularly useful in order to test the relationship between two variables as they affect clustering of incidents. However, in this study the results were less promising than had been desired. In fact, the dual kernel interpolation returned data that was completely unusable and unpresentable. There are several reasons which may explain why this occurred.

First, cases were limited to those that had the necessary geographic identifying information which resulted in 110 observations. Second, because the county in which this city resides is small, block-level data was not collected during the census, thus making the geographic areas of measure much larger in rural areas. Third, the geography of the city changes drastically from densely populated downtown block groups to rural block groups which are vastly larger than the downtown block groups. The great variability in block group areas made the dual kernel interpolation difficult because incidents occurring in these larger areas with much lower populations caused an artificial risk inflation for incidents occurring in those areas. The dual kernel analysis resulted in what appeared to be an inverted hot spot with densely populated areas in the downtown block groups showing low likelihood of clustering when accounting for the guardianship composite score. This method did not yield supportive evidence of the second hypothesis. However, when the single kernel interpolation is laid over the block groups with high composite scores, there is some visual evidence of interaction (see Figure 5). There definitely appears to be some sort of connection between high cluster areas of incidents and areas in the city with higher rates of single parent families and poverty. However, the dual kernel interpolation was not found to be the best statistical method for testing this relationship. Another attempted method returned in more telling results.

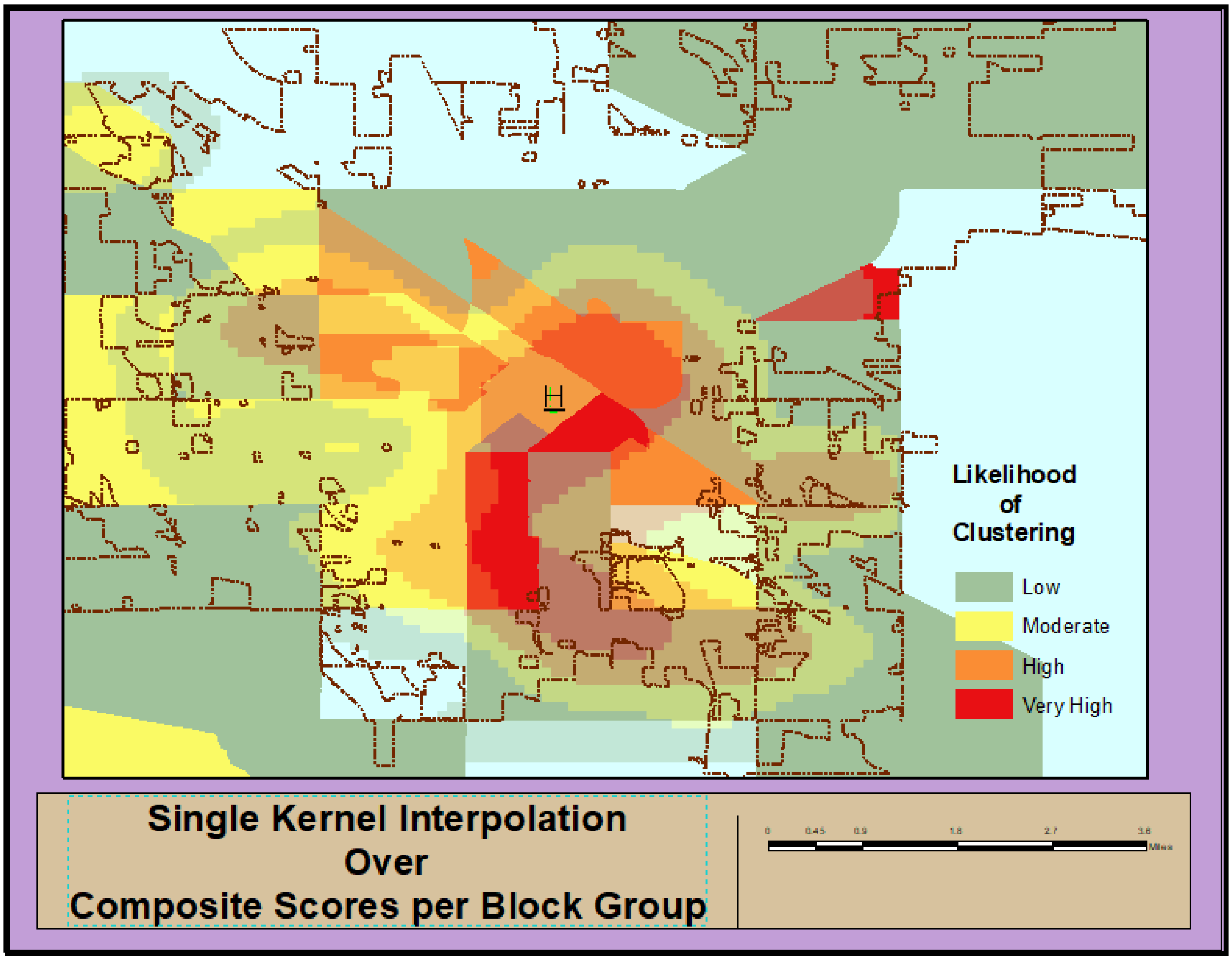

Figure 5. **Single Kernel Interpolation over Composite Scores per Block Group**

<u>Spatial Lag Regression</u>

For the block groups located within the city limits, spatial weights were calculated using GeoDa, a spatial statistics analytical software. Spatial weights measure the proximal distance between geographic units. A queen contiguity method was used to calculate the weight. Queen contiguity is a weight calculation method that includes common vertices of the geographic units instead of only immediate neighbors. As an example, if spatial weights were measured on a chess board, queen contiguity would draw paths to the eight grids around each grid, where a rook contiguity method would only draw 4. In this study, block groups immediately adjacent to another were weighted and the pathways between proximal block groups were mapped (see Figure 6). The figure demonstrates the connection paths between proximal block groups which allows for the calculation of spatial lag. The total number of block groups in the county from which census data was collected is 84. The minimum number of proximal neighbors was two, with a maximum of 11. The mean neighbor score was 5.79 and the median was five.

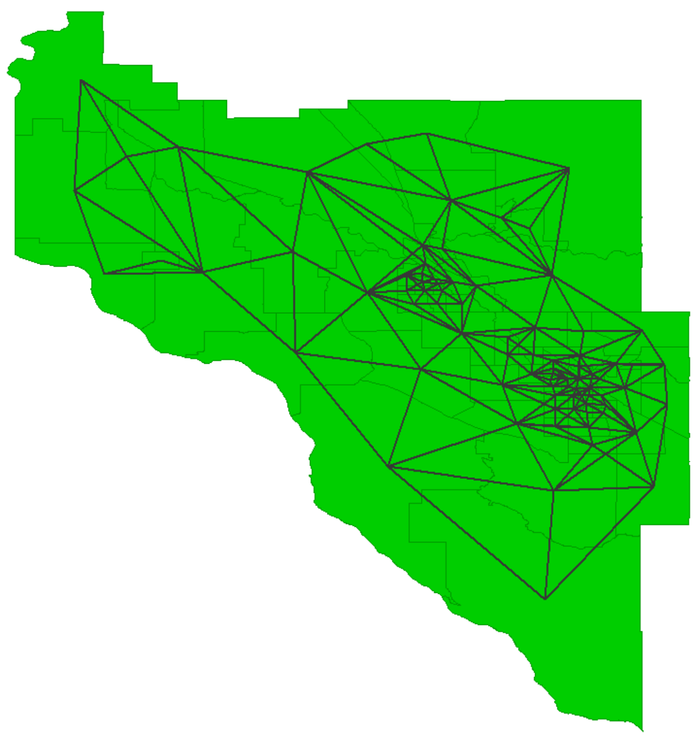

Figure 6. Connectivity Map of Proximal Block Group Neighbors

Once the mapping occurs, a lag score is calculated based on the incidents per block group in each geographic unit. This lag score is weighted by number of incidents and block group proximity based on the connectivity map. The spatial lag score is ultimately added to the dataset as a new variable linked to each geographic unit. The block groups that fell outside of the city limits were excluded from the dataset which left 46 remaining block groups.

Table 5. Spatial Lag Regression of CSA/SAAM Spatial Clustering

	B (SE)	β	*p*
Constant	3.146 (2.169)	—	0.155
Population Density	-0.486 (2.564)	-0.038	0.851
Male/Female Ratio	-0.298 (0.560)	-0.084	0.597
Minor Population	-0.191 (2.812)	-0.013	0.946
Minority Population	-1.108 (1.762)	-0.097	0.533
HS Graduate Rate	2.068 (1.787)	0.181	0.254
Residential Mobility	-3.165 (1.495)	-0.364	.041
Lack of Guardianship	2.866 (1.101)	.474	.013

The multivariate, spatial lagged regression was calculated using SPSS software. The model overall had a relatively low R^2 of 0.273 and a much lower adjusted R^2 of 0.095. The difference between the R^2 and the adjusted R^2 suggest that many of the independent variables do little to predict the occurrence of SAAM and CSA in geographic space. This is further demonstrated by the coefficient β. The results of the regression coefficients can be found in Table 5. Looking at the results from the various control variables included with the independent variable of concern, only two demonstrate statistical significance. Surprisingly, the variable measuring residential mobility shows a negative effect on the spatial lag, suggesting that areas with higher levels of mobility decrease the likelihood of spatial clustering. This was unanticipated as it contradicts what social disorganization theory would have predicted. The variable of concern, which is the lack of guardianship composite measure, resulted in a statistically significant positive effect which was expected. This effect is significant at the $p = .05$ alpha level with a standardized beta coefficient of 0.474, the highest coefficient effect of the tested variables, suggesting that the lack of guardianship measure does have a stronger and more positive influence on the spatial lag variable. The analyses resulted in strong support for the first hypothesis, and weak but significant evidence supporting the second hypothesis. These findings demonstrate a need to further understand spatial effects on the clustering of CSA and SAAM incidents.

CHAPTER FIVE: DISCUSSION

One area of interest in this study was the identification and separation of CSA and SAAM cases. This distinction was made primarily based on the age of the alleged perpetrator of the incident. Few attempts have been made to make this distinction, but it is important to do so because of the different circumstances of CSA and SAAM cases. In this study nearly 70% of the incidents were cases of CSA in which the offender was 18 years of age or older. Approximately 25% of the cases were SAAM, in which both the offender and the victim were less than 18 years old. This is noteworthy for several reasons. Finkelhor and colleagues (2014) found higher rates of SAAM than CSA in their sample of self-report surveys of juvenile sexual victimization. In this study, which relied on reported incidents to law enforcement, however, there was a heavy imbalance toward cases of CSA.

This raises important questions about the disclosure of victimization and the decision to report to law enforcement. This data would suggest that cases of CSA are much more prevalent, but contradicting data from the previously cited study would suggest the opposite. It is likely that CSA incidents are seen as more malicious by victims, witnesses, and guardians than SAAM cases due to the larger gap in age between the victims and the offenders. The average age difference in CSA cases was approximately 15 years and the average age difference for SAAM was only one year. It is possible that victims, witnesses, and guardians see SAAM cases, where the victim and suspect age are closer, as more related to juvenile sexual curiosity than criminal behavior;

perhaps they even assign more culpability to the victims in these cases. More research is necessary to examine differences in reporting behavior of cases that would be classified as SAAM compared to CSA.

In order to address the first hypothesis of this study, Moran's I statistic and a single kernel interpolation method were used to measure clustering of these incidents in geographic space. This was important because few, if any, have tested sexual violence perpetrated against minors for evidence of spatial clustering. The results showed strong support for the first hypothesis (see Figures 3 and 4). Moran's I calculations demontrated significant evidence of spatial autocorrelation and the single kernel interpolation created a visual representation of that clustering. Evidence of clustering is important for two primary reasons.

First, it allows future researchers the opportunity to ask deeper questions as to what variables influence clustering. Spatial autocorrelation is an important element in the explanation of criminal occurrence that has long been overlooked. With new spatial software programs and statistical methods, spatial autocorrelation can be calculated, measured, and assessed as part of the complete explanation. With evidence of clustering, researchers can try to understand different characteristics and environments which likely affect the formation of hotspots.

Second, it facilitates the appropriate allocation of resources to best respond to specific incidents of criminal behavior. In this instance, with regards to sexual crimes perpetrated against minors, it helps the local police department and non-profit social organizations know where to target specific intervention strategies, vital programs, and community aids in an effort to reduce sexual crime. To both demonstrate the effectiveness of and highlight the positive efforts from local law enforcement, the family justice center, which seeks to respond to these incidents among others, was represented on the GIS maps with an “H” symbol. The family justice center fell centrally in one of the hotter zones demonstrating the utility of its location. However, where the map can further benefit local agencies is in the southern spur of the hot zone. There appeared to be a secondary hot zone south of the primary downtown hotspot which had a high likelihood of incidence occurring. The distance from this area to the family justice center may be of particular interest to the law enforcement agency and other organizations. Similarly, there were hot zones directly east and northeast of the primary hot zone which fall distant from downtown resources. These hot zones are traditional residential areas. These areas are important to note as well, as proximity to resources can be a vital tool to help victims.

With positive results from the Moran’s I calculation, and a solid visual representation of hotspots, both independently and weighted by minor population, there is strong evidence of the clustering of both CSA and SAAM cases. This lends strong support to the first hypothesis, demonstrating that these types of sexual crimes cluster. Evidence of this nature opens the door to deeper analyses which aim to understand what factors influence clustering.

One method attempted in this study to measure what variables affect the clustering of CSA and SAAM incidents was a dual kernel interpolation. Unfortunately this ended up being a weaker method. The city under study in this analysis changes drastically from urban and densely populated at its center to quite rural and sparsely populated on the outer edges. Because there were generally few incidents throughout the city, although they clearly clustered in the center of the city, incidents that occurred in the rural areas resulted in a hyper-inflation of scores in those block groups. This would likely be a much more effective method of testing spatial influence in a city with a more consistent population spread. It is possible that a larger sample size would yield better results. In order to more appropriately test Hypothesis 2 with the city and data available in this study, a spatially lagged regression was tested.

Findings of note from the spatial lag regression were those concerning the lack of guardianship composite measure and residential mobility. As hypothesized, the lack of guardianship composite score, as measured through a composite score of poverty and ratio of children being raised by single parents, was a significant predictor of CSA/SAAM density after accounting for spatial autocorrelation. This demonstrated direct support for Hypothesis 2. This is not surprising as spatial research has consistently found that crime generally occurs more often in areas exhibiting socially disorganized characteristics (Shaw & McKay, 1942; Sherman et al., 1989). Although these characteristics have more often been associated with social disorganization as posited by Shaw and McKay (1942), the present study’s findings supports the concepts outlined in routine activity theory as well (Cohen & Felson, 1979; Cohen, et al., 1980).

Sexual crimes perpetrated against minors are strikingly unique as compared to many other crimes that are more regularly studied in this manner. Finkelhor’s (1984) preconditions model requires four elements before the sexual abuse of a child can occur: a sexually motivated offender, overcoming internal inhibitors, overcoming external barriers, and overpowering of the child’s resistance. What is fascinating here is the similarity to RAT in several respects. Both Finkelhor’s (1984) and Cohen and Felson’s (1979) work recognized the convergence of motivated offender and victim. Finkelhor

(1984) also draws similar theoretical lines in his description of the overcoming of external barriers and the resistance of the child. These components can easily be tied to lack of guardianship. Finkelhor (1984) argues that bigger, stronger, and more emotionally stable children do not make suitable targets for victimization because they can defend themselves against would-be perpetrators. Similarly, Finkelhor (1984) argues that well-supervised children who have strong relationships with their guardians are less likely to be selected as victims of sexual violence because those factors increase the odds of discovery and disclosure. By the same mode of thinking, children raised in lower socio-economic homes and in homes with less parental supervision would be more likely to be selected as victims because they are less guarded than their counterparts. What was observed in this study, with the significant relationship between the lack of guardianship composite measure and spatial weight, is that CSA and SAAM incidents are more likely to occur in spaces which have higher concentrations of those characteristics that diminish potential guardianship. Although we cannot claim unequivocal and overwhelming evidence of RAT in these cases, especially due to the low R^2 and adjusted R^2, a β of 0.474 does demonstrate at least some support for the relationship between lack of guardianship and these incidents.

The negative beta score of -0.364 associated with the residential mobility measure was entirely unexpected. Residential mobility is usually associated with increased criminality (see Sampson & Groves, 1989; Shaw & McKay, 1942). However, there was a slight negative relationship between the amount of movement in an area and the clustering of SAM and CSA incidents. Perhaps, this is explained by the fact that perpetrators need a significant amount of time to groom their victims. This could also be explained by the interpersonal nature of sexual crimes. Offenders are not likely to be strangers to the victims in these types of cases (Snyder, 2000). The overwhelming majority of CSA and SAAM incidents are committed by perpetrators known to the victim (Finkelhor, 1979, 1984; Snyder, 2000). This may explain why areas which experience less residential movement at the macro level may experience a slight increase in potential clustering.

CHAPTER SIX: LIMITATIONS AND CONCLUSION

Limitations

There are several notable limitations that affected this study. The first is the small sample size. Sexual victimization of children is underreported to law enforcement (Finkelhor, 1984; Finkelhor & Ormrod, 2001). This made the availability of data limited as we had to rely on those cases reported to the local police agency to obtain official location data of the incidents. Only 46 block groups were available within the city as well, limiting the sample for the spatial lag regression. Second, these cases were reported incidents, not verified, or convicted cases. Essentially, spatial lag and weights are measuring ripples from events. And it is important to note that the originating incidents, in many cases, were not confirmed events. In addition, given the low reporting rate of sexual victimization in general, an analysis based on self-reported incidents of victimization could reveal different results altogether. Third, block-level data was unavailable for the selected city, as well as some previously expected census data. Block group data was substituted. These areas are larger and therefore less accurate. Fourth, characteristics of environments do not always fit neatly into census geographic units (Baller, Anselin, Messner, Deane & Hawkins, 2001; Kubrin & Weitzer, 2003). Census geographic units are often rudimentary and do not represent actual neighborhood delineations. Fifth, the lack of guardianship composite measure was a proxy and does not directly measure lack of guardianship. Sixth, the data only spans two years of reported incidents, a more complete understanding of the variable interaction would be possible with a longer period of collected data. Finally, because these analyses focus on a specific location, there is no external validity, the findings here only apply to the location of study.

Future Research

Although the evidence in support of the second hypothesis is not overwhelming, there is enough to suggest the potential benefit of similar studies in the future. Studies which seek to address the sample size issue and test the spatial applicability of the theory in cities with more uniform geographic characteristics might prove more telling. The slight negative association between residential mobility and the spatial weight of these block groups merits further exploration as well, though it may be the result of a small sample size. If similar results are replicated with better data and in better places, it may answer questions about the utility of social disorganization theory as it pertains to the occurrence of the sexual victimization of juveniles.

Although the secondary spatial analyses did not prove as potent as was expected, the initial findings from the clustering analysis are greatly beneficial to the field, to local responding organizations, and demonstrate strong support for the first hypothesis. Law enforcement agencies, non-profit organizations and local governments will benefit from the knowledge that these incidents cluster as they determine the allocation of community resources to respond to these cases. Strong evidence of spatial clustering establishes that there are some geographic characteristics that may explain the clustering and future research should seek answers to that question, perhaps in different ways than were attempted here. Dual kernel interpolation may prove to be much more useful in areas with more available data from the U.S. Census Bureau and in a location with more population consistency across geographic units.

Conclusion

The primary purposes of this study were to address two hypotheses: to determine whether incidents of CSA and SAAM clustered in space and to test the applicability of the lack of guardianship element of RAT from a spatial analytical perspective. Strong and clear evidence of spatial clustering and the formation of hot spots was evident for CSA and SAAM incidents. Dual kernel interpolation, however, proved to be a weak method of deeper analysis with this particular dataset and location, however, spatial lag regression was more promising. A positive and statistically significant relationship was observed between the lack of guardianship composite score measure and the spatial lag variable indicating support for routine activity theory. This coupled with strong Moran’s I results demonstrate the apparent need for future research to reflect on the impact of space both as it relates to the sexual victimization of minors and other types of crime.

REFERENCES

Bailey, T. C., & Gatrell, A. C. (1995). *Interactive spatial data analysis* (Vol. 413). Essex: Longman Scientific & Technical.

Baller, R. D., Anselin, L., Messner, S. F., Deane, G., & Hawkins, D. F. (2001). Structural covariates of U.S. county homicide rates: Incorporating spatial effects. *Criminology*, *39*(3), 561-588.

Barr, R., & Pease, K. (1990). Crime placement, displacement, and deflection. *Crime and Justice*, *12*, 277-318.

Beccaria, C. (1995). *An essay on crimes and punishments*. Cambridge: Cambridge University Press.

Braga, A. A., Papachristos, A. V., & Hureau, D. M. (2014). The effects of hot spots policing on crime: An updated systematic review and meta-analysis. *Justice Quarterly*, *31*(4), 633-663.

Braga, A. A., Weisburd, D. L., Waring, E. J., Mazerolle, L. G., Spelman, W., & Gajewski, F. (1999). Problem-oriented policing in violent crime places: A randomized controlled experiment. *Criminology*, *37*(3), 541-580.

Brantingham, P., & Brantingham, P. (Eds.). (1981). *Environmental criminology* (pp. 27-54). Beverly Hills, CA: Sage Publications.

Brantingham, P., & Brantingham, P. (1993). Crime pattern theory. In *Environmental Criminology and Crime Analysis* (pp. 100-116). London: Willan.

Bywaters, P., Bunting, L., Davidson, G., Hanratty, J., Mason, W., McCartan, C., & Steils, N. (2016). *The relationship between poverty, child abuse and neglect: An evidence review.* York: Joseph Rowntree Foundation.

Cass, A. I. (2007). Routine activities and sexual assault: An analysis of individual-and school-level factors. *Violence and Victims*, *22*(3), 350.

Chainey, S.P., & Ratcliffe, J.H. (2005). *GIS and crime mapping.* London: Wiley.

Chainey, S., Tompson, L., & Uhlig, S. (2008). The utility of hotspot mapping for predicting spatial patterns of crime. *Security Journal*, *21*(1-2), 4-28.

Chaudry, A., & Wimer, C. (2016). Poverty is not just an indicator: The relationship between income, poverty, and child well-being. *Academic Pediatrics*, *16*(3), S23-S29.

Cho, S., Hong, J. S., Espelage, D. L., & Choi, K. S. (2017). Applying the lifestyle routine activities theory to understand physical and nonphysical peer victimization. *Journal of Aggression, Maltreatment & Trauma*, *26*(3), 297-315.

Cohen, L., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review,* 44, 588-607.

Cohen, L., & Cantor, D. (1980). The determinants of larceny. *Journal of Research in Crime and Delinquency*, 17*,* 140-159.

Cohen, L., Felson, M., & Land, K. (1980). Property crime rates in the United States: A macrodynamic analysis, 1947-1977. *American Journal of Sociology,* 86, 90-117.

Conger, R. D., Ge, X., Elder Jr, G. H., Lorenz, F. O., & Simons, R. L. (1994). Economic stress, coercive family process, and developmental problems of adolescents. *Child Development*, *65*(2), 541-561.

Crewdson, J. (1988). *By silence betrayed: Sexual abuse of children in America*. Boston: Little, Brown.

Daigle, L. E., & Muftic, L. R. (2015). *Victimology*. SAGE Publications.

De Francis, V. (1971). Protecting the child victim of sex crimes committed by adults. *Federal Probation*, *35*, 15. Washington D.C.

Eck, J. E. (1993). The threat of crime displacement. In *Criminal Justice Abstracts 25*(3), 527-546.

Eck, J., Chainey, S., Cameron, J., & Wilson, R. (2005). *Mapping crime: Understanding hot spots*. USA: National Institute of Justice.

Eck, J. E., & Weisburd, D. (1995). Crime and place. In *Crime prevention studies*. Monsey, NY: *Criminal Justice Press.*

Fergusson, D. M., Horwood, L. J., & Lynskey, M. T. (1996). Childhood sexual abuse and psychiatric disorder in young adulthood: II. Psychiatric outcomes of childhood sexual abuse. *Journal of the American Academy of Child & Adolescent Psychiatry*, *35*(10), 1365-1374.

Finkelhor, D. (1979). *Sexually victimised children*. New York: The Free Press.

Finkelhor, D. (1984). *Child sexual abuse: New theory and research*. New York: The Free Press, Macmillan.

Finkelhor, D., & Baron, L. (1986). Risk factors for child sexual abuse. *Journal of Interpersonal Violence*, 1(1), 43-71.

Finkelhor, D., Hotaling, G., Lewis, I., & Smith, C. (1990). Sexual abuse in a national survey of adult men and women: Prevalence, characteristics, and risk factors. *Child Abuse & Neglect*, *14*(1), 19-28.

Finkelhor, D., & Ormrod, R. (2001). Child abuse reported to the police. *Juvenile Justice Bulletin*, 1-8. Washington, DC: US Government Printing Office.

Finkelhor, D., Shattuck, A., Turner, H. A., & Hamby, S. L. (2014). The lifetime prevalence of child sexual abuse and sexual assault assessed in late adolescence. *Journal of Adolescent Health*, *55*(3), 329-333.

Franklin, C. A., Franklin, T. W., Nobles, M. R., & Kercher, G. A. (2012). Assessing the effect of routine activity theory and self-control on property, personal, and sexual assault victimization. *Criminal Justice and Behavior*, *39*(10), 1296-1315.

Gidycz, C. A., Coble, C. N., Latham, L., & Layman, M. J. (1993). Sexual assault experience in adulthood and prior victimization experiences: A prospective analysis. *Psychology of Women Quarterly*, *17*(2), 151-168.

Gorey, K. M., & Leslie, D. R. (1997). The prevalence of child sexual abuse: Integrative review adjustment for potential response and measurement biases. *Child Abuse & Neglect*, *21*(4), 391-398.

Gruber, K. J., & Jones, R. J. (1983). Identifying determinants of risk of sexual victimization of youth: A multivariate approach. *Child Abuse & Neglect*, *7*(1), 17-24.

Guerette, R. T., & Bowers, K. J. (2009). Assessing the extent of crime displacement and diffusion of benefits: A review of situational crime prevention evaluations. *Criminology*, *47*(4), 1331-1368.

Hall, G. C. N., & Hirschman, R. (1991). Toward a theory of sexual aggression: A quadripartite model. *Journal of Consulting and Clinical Psychology*, *59*(5), 662.

Henson, B., Wilcox, P., Reyns, B. W., & Cullen, F. T. (2010). Gender, adolescent lifestyles, and violent victimization: Implications for routine activity theory. *Victims & Offenders*, *5*(4), 303-328.

Hesseling, R. (1994). Displacement: A review of the empirical literature. *Crime Prevention Studies*, *3*(1), 97-230.

Hill, B., & Paynich, R. (2013). *Fundamentals of crime mapping*. Sudbury: Jones & Bartlett Publishers.

Illinois Criminal Justice Information Authority. (1996). *Spatial and temporal analysis of crime*. Springfield: State of Illinois.

Jensen, G. F., & Brownfield, D. (1986). Gender, lifestyles, and victimization: Beyond routine activity. *Violence and Victims*, *1*(2), 85.

Johnson, S. D., Guerette, R. T., & Bowers, K. (2014). Crime displacement: What we know, what we don't know, and what it means for crime reduction. *Journal of Experimental Criminology*, *10*(4), 549-571.

Jones, L., & Sumnall, H. (2016). Understanding the relationship between poverty and alcohol misuse. *Liverpool: Liverpool John Moores University*, 9-17.

Kennedy, L. W., & Baron, S. W. (1993). Routine activities and a subculture of violence: A study of violence on the street. *Journal of Research in Crime and Delinquency*, *30*(1), 88-112.

Kennedy, L. W., & Forde, D. R. (1990). Routine activities and crime: An analysis of victimization in Canada. *Criminology*, *28*(1), 137-152.

Kercher, G. A., & McShane, M. (1984). The prevalence of child sexual abuse victimization in an adult sample of Texas residents. *Child Abuse & Neglect*, *8*(4), 495-501.

Kubrin, C. E., & Weitzer, R. (2003). New directions in social disorganization theory. *Journal of Research in Crime and Delinquency*, *40*(4), 374-402.

Kuipers, M. A., Jongeneel-Grimen, B., Droomers, M., Wingen, M., Stronks, K., & Kunst, A. E. (2013). Why residents of Dutch deprived neighbourhoods are less likely to be heavy drinkers: The role of individual and contextual characteristics. *Journal of Epidemiology and Community Health*, *67*(7), 587-594.

Levine, N. (2006). Crime mapping and the Crimestat program. *Geographical analysis*, *38*(1), 41-56.

Levine, N. (2002). *A spatial statistics program for the analysis of crime incident locations*. Ned Levine and Associates, Houston, TX, and the National Institute of Justice, Washington, DC.

Lodico, M. A., Gruber, E., & DiClemente, R. J. (1996). Childhood sexual abuse and coercive sex among school-based adolescents in a midwestern state. *Journal of Adolescent Health*, *18*(3), 211-217.

Magnuson, K. A., & Duncan, G. J. (2002). Parents in poverty. In M. Bornstein (Ed.), *Handbook of parenting, 4* (95-121). New Jersey: Lawrence Erlbaum Associates.

Maker, A. H., Kemmelmeier, M., & Peterson, C. (2001). Child sexual abuse, peer sexual abuse, and sexual assault in adulthood: A multi-risk model of revictimization. *Journal of Traumatic Stress*, *14*(2), 351-368.

Mannon, J. M. (1997). Domestic and intimate violence: An application of routine activities theory. *Aggression and Violent Behavior*, *2*(1), 9-24.

Marshall, W. L., & Barbaree, H. E. (1990). An integrated theory of the etiology of sexual offending. In *Handbook of sexual assault* (pp. 257-275). Boston: Springer.

Matheson, F. I., White, H. L., Moineddin, R., Dunn, J. R., & Glazier, R. H. (2012). Drinking in context: The influence of gender and neighbourhood deprivation on alcohol consumption. *Journal of Epidemiology and Community Health*, *66*(6), e4-e4.

Messman, T. L., & Long, P. J. (1996). Child sexual abuse and its relationship to revictimization in adult women: A review. *Clinical Psychology Review, 16*(5), 397-420.

Miethe, T. D., Stafford, M. C., & Long, J. S. (1987). Social differentiation in criminal victimization: A test of routine activities/lifestyle theories. *American Sociological Review*, 184-194.

Miller, P. Y. (1976). *Blaming the victim of child molestation: An empirical analysis*. Doctoral dissertation, Northwestern University.

Olafson, E., Corwin, D. L., & Summit, R. C. (1993). Modern history of child sexual abuse awareness: Cycles of discovery and suppression. *Child abuse & neglect*, *17*(1), 7-24.

Openshaw, S. (1984). The modifiable areal unit problem. In *Concepts and Techniques in Modern Geography 38*. Norwich, UK: Geobooks.

Pereda, N., Guilera, G., Forns, M., & Gómez-Benito, J. (2009). The prevalence of child sexual abuse in community and student samples: A meta-analysis. *Clinical Psychology Review,* 29(4), 328-338.

Planty, M., Langton, L., Krebs, C., Berzofsky, M., & Smiley-McDonald, H. (2016). *Female victims of sexual violence.* U.S. Department of Justice, Bureau of Justice Statistics. Available at https://www.bjs.gov/content/pub/pdf/fvsv9410.pdf.

Putnam, F. W. (2003). Ten-year research update review: Child sexual abuse. *Journal of the American Academy of Child & Adolescent Psychiatry*, *42*(3), 269-278.

Ratcliffe, J. H., Taniguchi, T., Groff, E. R., & Wood, J. D. (2011). The Philadelphia foot patrol experiment: A randomized controlled trial of police patrol effectiveness in violent crime hotspots. *Criminology*, *49*(3), 795-831.

Rosenblatt, K. (2017, November 29). Ex-gymnastics doctor Larry Nassar pleads guilty to 3 more criminal sex charges. *NBC News.* Retreived from https://www.nbcnews.com/news/us-news/ex-gymnastics-doctor-larry-nassar-pleads-guilty-3-more-criminal-n824861

Russell, D. E. (1983). The incidence and prevalence of intrafamilial and extrafamilial sexual abuse of female children. *Child Abuse & Neglect*, *7*(2), 133-146.

Sampson, R. J. (1987). Urban black violence: The effect of male joblessness and family disruption. *American Journal of Sociology*, *93*(2), 348-382.

Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology*, *94*(4), 774-802.

Sampson, R. J., & Wooldredge, J. D. (1987). Linking the micro-and macro-level dimensions of lifestyle-routine activity and opportunity models of predatory victimization. *Journal of Quantitative Criminology*, *3*(4), 371-393.

Schreck, C. J., & Fisher, B. S. (2004). Specifying the influence of family and peers on violent victimization: Extending routine activities and lifestyles theories. *Journal of Interpersonal Violence*, *19*(9), 1021-1041.

Schwartz, M. D., DeKeseredy, W. S., Tait, D., & Alvi, S. (2001). Male peer support and a feminist routing activities theory: Understanding sexual assault on the college campus. *Justice Quarterly*, *18*(3), 623-649.

Schwartz, M. D., & Pitts, V. L. (1995). Exploring a feminist routine activities approach to explaining sexual assault. *Justice Quarterly*, *12*(1), 9-31.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. Chicago: University of Chicago Press.

Seccombe, K. (2000). Families in poverty in the 1990s: Trends, causes, consequences, and lessons learned. *Journal of Marriage and Family*, *62*(4), 1094-1113.

Sherman, L. W., Gartin, P. R., & Buerger, M. E. (1989). Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology*, *27*(1), 27-56.

Sherman, L. W., & Rogan, D. P. (1995). Effects of gun seizures on gun violence: "Hot spots" patrol in Kansas City. *Justice Quarterly*, *12*(4), 673-693.

Sherman, L. W., & Weisburd, D. (1995). General deterrent effects of police patrol in crime "hot spots": A randomized, controlled trial. *Justice Quarterly*, *12*(4), 625-648.

Snyder, H. N. (2000). *Sexual assault of young children as reported to law enforcement: Victim, incident, and offender characteristics*. Washington DC: U.S. Department of Justice.

Söchting, I., Fairbrother, N., & Koch, W. J. (2004). Sexual assault of women: Prevention efforts and risk factors. *Violence Against Women*, *10*(1), 73-93.

Summit, R., & Kryso, J. (1978). Sexual abuse of children: A clinical spectrum. *American Journal of Orthopsychiatry*, *48*(2), 237.

Steele, H., Bate, J., Steele, M., Dube, S. R., Danskin, K., Knafo, H., ... & Murphy, A. (2016). Adverse childhood experiences, poverty, and parenting stress. *Canadian Journal of Behavioural Science/Revue*, *48*(1), 32.

Tewksbury, R., & Mustaine, E. E. (2001). Lifestyle factors associated with the sexual assault of men: A routine activity theory analysis. *The Journal of Men's Studies*, *9*(2), 153-182.

U.S. Census Bureau. (2010). *Standard Hierarchy of Census Geographic Entities.* Retrieved from https://www2.census.gov/geo/pdfs/reference/geodiagram.pdf?#

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, et al.(2017). *Child maltreatment*. Retrieved from: https://www.acf.hhs.gov/sites/default/files/cb/cm2017.pdf#page=15.

Walker, B. B., Schuurman, N., & Hameed, S. M. (2014). A GIS-based spatiotemporal analysis of violent trauma hotspots in Vancouver, Canada: Identification, contextualisation and intervention. *BMJ Open*, *4*(2), e003642.

Ward, M. D., & Gleditsch, K. S. (2018). *Spatial regression models* (Vol. 155). Thousand Oaks: Sage Publications.

Ward, T., & Siegert, R. J. (2002). Toward a comprehensive theory of child sexual abuse: A theory knitting perspective. *Psychology, Crime and Law*, *8*(4), 319-351.

Weisburd, D., & Green, L. (1995). Policing drug hot spots: The Jersey City drug market analysis experiment. *Justice Quarterly*, *12*(4), 711-735.