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Communications and Methodologies in Crime Geography: Contemporary Approaches to Disseminating Criminal Incidence and Research

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Communications and Methodologies in Crime Geography: Contemporary Approaches to Disseminating Criminal Incidence and Research

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by

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ABSTRACT

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Many tools exist to assist law enforcement agencies in mitigating criminal activity. For centuries, academics used statistics in the study of crime and criminals, and more recently, police departments make use of spatial statistics and geographic information systems in that pursuit. Clustering and hot spot methods of analysis are popular in this application for their relative simplicity of interpretation and ease of process. With recent advancements in geospatial technology, it is easier than ever to publicly share data through visual communication tools like web applications and dashboards. Sharing data and results of analyses boosts transparency and the public image of police agencies, an image important to maintaining public trust in law enforcement and active participation in community safety.

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CHAPTER 1

INTRODUCTION

History of Geographic Research in Criminology

The empirical study of crime is a relatively new field compared to other social sciences, and has a tumultuous history full of highs and lows. Emerging out of early 19th century Europe, statisticians eagerly applied judicial data on juvenile delinquents and adult criminals to census demographics (e.g., Alison (1840), Holland (1843), Guerry (2002). At first looking at broad, countrywide distributions of crime rates, researchers analyzed data at regional and city levels to determine the cause of high crime rates in the fast-growing industrial centers of Europe.

Emergence of Empiricism in the Study of Crime

The origin of the serious scientific inquiry into the relationship between criminality and place coincides with the first government publications of official crime statistics in 1825 (Voss and Petersen 1971). France and England, most notably, were among the first countries to publicly release judicial data regarding criminal and delinquent offenses. These data were comprehensive in that they included incidents and their circumstances in addition to data on the offending party such as their place of residence. Andre-Michel Guerry is among the first credited in the research of "moral statistics" on a large-scale. In his 1833 *Essai sur la Statistique Morale de la France,* Guerry compiles data and draws geographic comparisons between crime and the demography of French departments; Guerry included variables such as age, sex, and education in his analyses. Based on his findings, Guerry theorized that crime is influenced by poverty, lack of education, and population density (Voss and Petersen 1971; Guerry 2002). Many other studies in the so-called "Cartographic School" era of the 19th century cross-referenced offender data with census statistics to investigate causal or proxy variables contributing to the high presence of crime in a region. The naming of this period of growth in the science of criminality comes from the widespread use of maps to visualize the spatial differences in crime rates, something seen as a novel innovation at the time (Voss and Petersen 1971).

Prior to the release of official data on crime, the subject of criminology was a topic of philosophy and political economy. The topics of discussion were largely on the efficacy of laws in effect at the time and potential benefits of implementing new laws. These social philosophers held many hypotheses on crime and law with no scientific inquiry or solid methodologies to evaluate and confirm them (Levin and Lindesmith 1971; Brantingham and Brantingham 1991a). Some in the Cartographic School held contempt for these predecessors. Henry Mayhew, an English statistician, once called them "a sect of social philosophers who sat beside a snug sea-coal fire and tried to think out the several matters affecting the working classes…retired to some obscure corner, and there remained, like big-bottomed spiders, spinning their cobweb theories among heaps of rubbish" (Levin and Lindesmith 1971).

English researchers, philosophers, and law officials continued adding theories and literature to the emerging field between 1830 and 1860 with a focus on regional and local studies of crime (Alison 1840; Holland 1843; Levin and Lindesmith 1971). A common link between studies was the concentration of juvenile delinquents and adult criminals in deteriorated sections of large towns and cities. The impact on population from England's growth into an industrial nation was noticed by contemporary observers who saw crime and immorality inseparable from factories, the harshness of cramped urban streets and alleys, and the poorly-ventilated living spaces, all of which the working class became accustomed to out of their desperate circumstances (Holland 1843). The governor of Coldbath Prison in London said that housing conditions were in a "state of frightful demoralization" and was the principal cause of crime and delinquency in the inner city (Levin and Lindesmith 1971). Alison (1840) authored multiple volumes on poverty, vice, and the human pursuit of happiness, writing an extensive chapter on the effects of vice on the urban poor. As was common during the Industrial Revolution, impoverished families from rural areas migrated to cities and crammed together out of desperation, perhaps with the likes of drunks, thieves, and prostitutes. Alison gives an anecdote of one such hard-working family, coming home to witness seemingly joyous persons reveling in licentious and immoral behavior, and the want for present enjoyment coupled with the contagious nature of bad example compelling them to join in the euphoria surrounding them. The boys become thieves, girls becomes prostitutes, resulting in one day being arrested by the police for their crimes. Such a situation comes not from the depravity of their character but the temptations they were exposed to by their circumstances (Alison 1840). Matthew D. Hill posited that areas with larger populations lack a "natural police" that smaller and rural communities have. This natural order has some wholesome influence originating from the closeness in both proximity and relationship between people in those communities regardless of any social factor (Levin and Lindesmith 1971). Due to the large number of individuals with a diaspora of experiences, standards, and values, not to mention the separation between poor working class housing and relatively expensive more comfortable housing, that natural police does not manifest in the working class sections of the city (Levin and Lindesmith 1971).

The Cartographic Era of spatial criminal inquiry ended with the rise of Italian physician Cesare Lombroso into prominence in the field. In Lombroso's 1876 *L'uomo Delinquent* [Criminal Man], he expressed the controversial theory that criminals are a distinctive physical type and are biologically defective or otherwise genetically predisposed to a life of crime. Lombroso described the "Criminal Man," like the primitive Man, as one with abundant hair, sparse beard, a receding forehead, large ears, and oblique eyes, among other traits (Voss and Petersen 1971; Lombroso 2006). Lombroso's hypothesis of "theoretical impotence," that the criminal is an automaton destined to a path of deviant behavior, attracted physicians and psychologists to criminology despite widespread criticism from contemporary criminologists as this theory countered the notion of free will and was ignorant to social and economic factors which were believed to be the main contributors to crime. Compelled by these critics, Lombroso revised his theory, now accounting for social impacts (Morris 1957). The influx of these researchers into criminology with backgrounds widely different from the likes of Guerry and Mayhew led to something of an eclipse altering the progression of criminology and shifting the focus of criminology to the offender. This went so far as to overshadow previous researchers, causing Lombroso to be mistakenly labelled as the progenitor of criminology (Levin and Lindesmith 1971; Voss and Petersen 1971; Lombroso 2006).

The Chicago School and Social Ecology

In the late 19th and early 20th century, the city of Chicago became a frontline in social science due to a rapidly growing immigrant population. Researchers at the Chicago School of Sociology became concerned with the relationships between populations sharing the same living space and the character of that territory, i.e., social structure in relation to the local environment, a subject that would become known as "social ecology." Upon its introduction, social ecology concerned itself with two elements: social conflict due to usually scarce resources in an industrialized urban area and the nature and quality of social organization in these areas (Butorac and Marinović 2017). This became the guiding focus for researchers at the School, who studied social ecology through the lens of criminology.

Compared to the Cartographic Era of criminology, the "Chicago School Era" differentiates itself through questions regarding socio-criminal theories. Robert Park and Ernest Burgess created a framework through which their colleagues could understand the social roots of crime, dividing the city into five concentric zones surrounding a central core based on their distinguishing characteristics (Porter 2010; Burgess 2019). Park & Burgess predicted that crime rates were inversely proportional to the distance from city center (Harries 1974; Brantingham and Brantingham 1991a; Butorac and Marinović 2017). Of the zones Park and Burgess proposed in their Concentric Zone theories, the second zone, the Transition Zone, was of greatest interest to the Chicago School. Burgess, Park, and their colleagues hypothesized that the presence of deteriorated housing, abandoned buildings, industrial zones, and immigrant populations were predictors of crime, which were present in the Transition Zone (Porter 2010; Burgess 2019).

Clifford Shaw and Henry McKay worked to confirm the Concentric Zone Theory, and in doing so found delinquency flourishing in the Transition Zone. This was the case in not just Chicago, where they originally studied, but also in Birmingham, Cleveland, Denver, Philadelphia, Richmond, and Seattle; each city displayed similar geographic gradients in crime rates (Morris 1957). Further, Shaw and McKay found neighborhood or social organization a factor in juvenile delinquency, i.e., growth, transiency, heterogeneity, and poverty generates disorganized communities with rampant delinquency (Byrne 2016). Areas of social disorganization in a city are lacking in social controls and have a prominent criminal culture, showing a lack of community resistance to deviant behavior (Morris 1957). In the understanding of the social context in which juvenile delinquents lived, Shaw and McKay believed the origin of delinquency could be found (Byrne 2016).

The research of Shaw and McKay launched the sociology of crime into prominence, but it was not without critique. Sophie Robison questioned the validity of Shaw's delinquency rates under the belief that court appearances are not sufficiently reliable to determine the extent of delinquent behavior. However, Robison's definition of delinquency went beyond Shaw's, who did not consider anti-social (but legal) acts that go against the interests of the community as delinquent (Morris 1957; Robison 1960). Robison points out that the presence of unofficial community resources (e.g., religious organizations), which remediate poor behavior before the delinquent encounters the law, can cause underestimation of delinquent behavior in a community (Robison 1960). Shaw and McKay rebutted that by including those delinquents referred to community or private resources, it is no greater an index of total delinquent behavior for that (Shaw and McKay 1969). Robison additionally questioned if differences in community ethnic homogeneity or the distribution of police influenced rates in certain sections, as Shaw and McKay made no mention of those effects (Robison 1960). Similarly, C. T. Jonassen questioned if changes in police policies had any effect on the rate of apprehension of juvenile delinquents. Jonassen directed another criticism to Shaw and McKay through the validity of their comparisons over time, pointing out inconsistencies within their 30-year comparison of Chicago delinquency rates. Datasets from studies used for comparison described delinquents of varying age ranges (e.g., 10-15, 10-16, 10-17), a complication resulting from changes in the juvenile court system. Jonassen also viewed the census tract unit too large an aggregate for study, as they may include multiple culturally distinct neighborhoods (Morris 1957).

The Chicago School Era was a time of advancement in the theoretical and methodological frameworks further showing the importance of a space/environmental perspective in crime analysis. However, some modern criminologists claim that Shaw and

McKay's research were not supportive of a total examination of ecological theory of crime, given their focus on the criminal and no other environmental influence (Brantingham and Jeffery 1991).

The mid-19th century would become a stagnating time for criminology after the introduction and widespread implementation of factor analysis. A 1954 study of Baltimore by Bernard Lander attracted attention from his contemporaries with the claim that variables of "anomie" or social instability (e.g., overcrowded and substandard housing), not socio-economic status, were the major determinants of delinquency (Bordua 1958; Davidson 1981). However, labels of anomic and socio-economic are arbitrary and leads to the question of whether an anomic variable lacks socio-economic meaning and vice versa (Rosen and Turner 1967). While other researchers attempted to replicate his results with mixed success, most took issue with Lander's definition of anomie, his results, and choice of indicators. Lander's critics challenged him on the basis that delinquency is a product of anomie and Lander's methods and factor analysis were considered dead ends for criminology (Bordua 1958; Rosen and Turner 1967; Davidson 1981).

Revitalization and Environmental Criminology

In the early 1970s, another shift in criminology brought new life to the subject. C. R. Jeffery's *Crime Prevention through Environmental Design* and Oscar Newman's *Defensible Space: Crime Prevention through Urban Design* turned criminologists away from studying the criminal and towards the study of crime itself and the environmental factors that open up the opportunity for the commitment of that crime (Brantingham and Brantingham 1991a; Butorac and Marinović 2017). Researchers in "environmental criminology" study the characteristics of a criminal act; the criminal, the rationale for the crime site, and what creates the opportunity (Kim et al. 2013). Jeffrey and Newman's works attracted architects, environmental psychologists, geographers, and urban planners into a field dominated by psychologists and sociologists. Theories of environmental design, the way people interact with the urban spatial structure, and perception of criminal opportunity (as opposed to motivation), drove the literature forward. For example, Brantingham and Brantingham (1991b) state that cities where work areas shift from the core to the fringe areas tend to see an increase in crime on the periphery. The concept of an individual's "awareness space," their everyday surroundings, was central to the crime pattern theory where criminal acts occur during the everyday activities of a person's life. Danish researcher David Sorensen added that some crime types, like burglary, have a distance decay effect between a criminal's residence and the site of a crime, and the criminal typically avoids such activity within the immediate area of their residence (Butorac and Marinović 2017).

Geography and Geospatial Science in Law Enforcement

Planning is essential to creating effective policies, policing is no different. The usage of spatial analytics and geographic intelligence enhances police knowledge of general crime trends. The geographic profiling of criminals has been a resource for law enforcement for tracking down areas where serial offenders likely live by analyzing crime scenes using a distance decay function (Center for Geospatial Intelligence and Investigation; Harries 1999; LeBeau and Leitner 2011). Based off the work of environmental criminologists, distance decay in crime conveys the theory that criminals take shorter journeys, on average, to future crime sites. Geographic profiling works best as a decision support tool, filtering data for investigations of higher-profile repeat offenders (Center for Geospatial Intelligence and Investigation; Harries 1999).

Crime data are not just useful for police departments, but also for the public at large. Open, publically-accessible, datasets have the benefit of boosting public awareness and potentially reducing victimization (Assiniboine Community College Police Studies). With this goal, the Brandon Police Service (BPS) of Brandon, Manitoba created a mapping application using a web application development platform from the Environmental Systems Research Institute (ESRI). The application provides a wealth of geographic data on crimes against persons and property in the city and displays a “heat” surface where concentrated areas of crime are distinguishable on the map. While there are multiple disclaimers against using the application for judgment of safe or unsafe areas it still supplies useful statistics for managing police resources and personnel, boosting public awareness of local crime, and giving a measure of transparency to police activity (Assiniboine Community College Police Studies; Brandon Police Service 2019).

Community and Public Awareness Impacts

As the Chicago School found, public perception of crime and law enforcement affects the community’s response to crime trends and their relationship with local police. Crime policy in the United States is shaped by public views and political ideology, a phenomena easily discerned by the ongoing debates over gun legislation in response to “mass shootings” (Roberts and Stalans 1995; Luca et al. 2019). This relationship could be seen as either good or bad with statistics and surveys consistently finding conflict between the reality of overall crime trends and public perception of crime (Gramlich 2016; LaFree 2018). Researchers attribute blame for this inconsistency to news media and the sometimes sensationalized incidents of crime (Jackson and Gray 2010). Roberts and Stalans (1995) postulated that televised trials contribute to the media’s comparatively greater closeness to crime and justice, while surveys and data do not get as high a profile of coverage.

The role of police and the community in crime control is a contentious debate in the criminal justice community (Kelling and Wilson 1982; Harcourt 2001; Lombardo and Lough

2007; Hinkle 2009). Police and social scientists agree that a link exists between disorder and crime; if a broken window exists and is left untended, every window in the building will eventually break (Kelling and Wilson 1982). Known as the Broken Windows Theory, this method of policing centers around the crackdown on lesser offenses (e.g. public nuisance and negligence) to evoke a positive change in more serious crimes. Broken Windows originates from a quality-of-life improvement program in New Jersey, taking police out of patrol cars and putting them on walking beats. These beats had little or adverse impacts on the crime rates in the study cities but had the benefit of alleviating fear of crime and created a more favorable opinion of police officers in those areas. The police presence maintained a public order, keeping disorderly people (e.g. drunks/addicts, transients, etc.) in check, giving the public a false perception of safety. Another phrase coined for this strategy of policing is “order-maintenance” due to that perception.

One case of the Broken Windows theory in action is that of Stanford psychologist Philip Zimbardo. Zimbardo found after parking one automobile in the Bronx without its license plates and hood raised and another similar car in Palo Alto, California. People stole everything in the Bronx car within 24 hours, later vandals destroyed the car, and after then children used the wreckage as a playground. Nothing happened to the Palo Alto car for over a week until Zimbardo took a sledgehammer to it and others joined in, destroying the vehicle. Regardless of where the untended property was left, Zimbardo found, it led to deviant behavior and a breakdown of community controls (Zimbardo 1969).

Critics of the Broken Window theory, namely Bernard Harcourt (2001), cite the theory lacks sufficient evidence and the few experiments which state a positive result for Broken Window usually have some issues. One study of New York crime in the 1990s after implementing order-maintenance sweeps, where police heavily cracked down on misdemeanors in an effort to reduce serious crime, showed a remarkable drop in crime. However, cities across the U.S., including those without order-maintenance policing, were experiencing the same drop in crime. Harcourt criticized the study further by pointing out that an increase in police numbers, favorable economic trends, a drop in the young adult population, and a number of other factors likely influenced the change. Even if these quality of life programs contributed to drops in crime, he contests that it is likely the increased surveillance and aggressive stop-and-frisks and misdemeanor arrests (Harcourt 2001).

The perceived benefits of a crackdown on misdemeanors and other aggressive police policies (e.g. stop-and-frisk, zero-tolerance) on crime rates and arrests comes at the cost of public perception. These aggressive strategies put law enforcement at odds with communities, especially minorities. The stop-and-frisk policies of New York police departments are notorious for accusations of racial bias and discrimination (Gelman et al. 2007; White and Fradella 2016). On California's three strike laws, some argue it violates double jeopardy rules since it effectively punishes people further for previous offenses. For prior offenders who come of age, their juvenile crimes follow them into adulthood, potentially landing a young adult into a lengthy prison sentence for something they did as a child, circling back to the double jeopardy argument (Vitiello 1997). Despite the popularity of Broken Windows and the law enforcement strategies that came from it among police, support (both academic and popular) for it is mixed at best.

An alternative to cracking down on certain types of crime is a more community-driven approach to the crime problem. If public perception and social organization are known to have an impact on crime rates and the ability of law officers to do their jobs, would it prove beneficial to collaborate with citizens to remedy community problems related to local crime? Questions like this drive the “community implant” hypothesis, which focuses on increasing social controls in areas where it is weak or non-existent through collective action (individual or organizational) and community building. Additionally, this theory has the goals of increasing satisfaction with the police and give residents a sense of responsibly with community order “implanting” informal social controls (Lombardo and Lough 2007). Some police agencies today use strategies like this, placing focus on community relations and responding to local needs and problems (Johnson City Police Department 2018).

Study Objectives

Using the city of Johnson City, Tennessee, a community of 66,778 people (July 2018 estimate) in southern Appalachia, as the study area, an exploration of municipal-level trends in crime may give insight into the distribution of offenses in the city’s space (United States Census Bureau 2018). A distinction between areas of high crime of a particular type during a certain time of the day, or year, can be taken under the consideration of law enforcers to maintain and distribute resources to mitigate local issues. While police can find such information useful for their operations, the public may also find easily accessible information on local crime relevant to their quality of life. A web application can present a meaningful interface where police can interact with citizens by supplying information about the crime in their city.

The aims of this research are, therefore, to:

1. Analyze trends in local crime to determine when and where crimes concentrate.
2. Determine an effective medium for the dissemination of crime data.

CHAPTER 2

OBSERVATION OF CLUSTERS AND POINT INTENSITIES IN JOHNSON CITY, TN CRIME THROUGH NEAREST NEIGHBOR HIERARHICAL CLUSTER ANALYSIS AND KERNEL DENSITY ESTIMATION

Mitchell S. Ogden, Dr. T. Andrew Joyner, Dr. Ingrid Luffman, Dr. Joseph B. Harris

Abstract

Statistics and spatial analysis methods have long provided useful tools in parsing crime data to solve a variety of issues, from where criminals live to where concentrations of crime occur, at many scales. Cluster and hot spot analyses are relatively accessible methodologies in theory, application, and interpretation for analysts to implement, deducing areas where crimes occur in unusually close proximity or in high concentrations related to elsewhere within a city of study. While most agencies and researchers focus on analyzing raw data, adjusting to account for ambient daily population may grant additional insight into areas that are especially active despite sparse daily activity. This collection of spatial clustering and density methods coupled with a temporal exploration of the same data provides an overall picture of local crime trends. Using these results can better inform decision-makers in law enforcement agencies on resource allocation and assist police in community partnerships to find ways to curtail the apparent and underlying causes of crime.

Keywords: cluster, nearest neighbor hierarchical clustering, hot spot, kernel density estimation, crime statistics

Introduction

Spatial Techniques in Law Enforcement

Geographic Information Systems (GIS) provide effective tools and methods for visualizing patterns in criminal activity through spatial analysis. Since the 1960s, law enforcement agencies implemented cartographic methods, spatial analyses, and eventually GIS to answer questions relevant to crime patterns.

Journey-to-Crime. Criminal geographic profiling has a long history in law enforcement for its use in determining potential residential areas for serial offenders. Based on the concept that criminals do not deviate far from their routine activity to commit an offense, journey-to-crime uses a distance-decay function to eliminate areas unlikely to fit within an offender's awareness space as a support tool to prioritize areas for police to watch (Kent et al. 2006).

Wiles and Costello (2000) of the United Kingdom's Home Office analyzed advancements in transportation over the last three decades to determine if this expanded the distance criminals travel to commit a crime. They found that journeys are still typically short, and farther locations tend to have some connection to the offender (e.g., a leisure location). Wiles and Costello then identified the need for additional research on specific "professional" offenders and mapping of concentrated areas of victimization (Wiles and Costello 2000; Costello and Leipnik 2003).

Machine Learning. With advancements in technology, computers became powerful enough to calculate large, complex datasets in a wide variety of disciplines. A popular topic among computer and data scientists is Machine Learning (ML) where advanced computational hardware and software are used to process a dataset and develop "rules" to classify potential new observations. For example, in ecological modeling, ML is implemented to determine a species' potential habitat range based on recent observations of that species and related variables (e.g., climate) (Franklin 2010; McClendon and Meghanathan 2015). That logic could apply to crime as a “species” to determine anomic, socio-economic, and other variables influencing crime in an area, bringing the concept of criminal ecology full circle from Shaw & McKay (1969) during the Chicago School era of criminology.

The police of Vancouver, British Columbia, Canada (VPD) conducted a pilot test using a ML technique to combat residential burglaries in the city. Machine Learning determined areas most susceptible to future break-and-enters based on citizen reporting, which determined where the department prioritized sending patrols. During the quarter when they implemented the technique, the VPD reported the highest occurrence of break-and-enters in 20 years. The second quarter, it was reduced to the lowest in 25 years. Since then the department made this resource a staple of their management system, resulting in an effective police force (Beck 2019).

Risk Terrain Modeling. Researchers from Rutgers University developed the Risk Terrain Model (RTM) in response to a State Police request for a robust analysis of data related to their operations against crime in Irvington, NJ. The police gave the Rutgers team data on known residences of gang members, drug arrests, infrastructure, and shooting locations. A spatial relationship between drug arrests and known gang residences, and shootings were found to occur around gang residences or liquor stores, bars, strip clubs, and fast food restaurants. Seeing these connections, they created a composite map to identify what locales hold potential for future shootings. The risk terrain map closely matched the 18-month dataset, but since they were uncertain of the predictive capability of the technique, they partitioned the data into 6-month periods. Between the different time periods, they found that shifts in police activity matched the movement of shootings (Kennedy et al. 2009; Caplan and Kennedy 2011). Since then Caplan, Kennedy, and other researchers at Rutgers further developed RTM and how crimes of different types correlated to other factors like proximity to certain infrastructure (e.g., transportation) or other types of crime, socioeconomic variables, social disorganization, etc. (Caplan et al. 2011).

Outside academia, law enforcement utilizes RTM in predictive analysis of crime to prioritize resource expenditure in areas of elevated risk. The Baton Rouge Police Department makes use of a web dashboard with quarterly RTMs to target areas for patrols, engage the community and improve relations, and determine local attractors of crime in an attempt to reduce neighborhood crime rates, improve reporting, and alleviate fear of crime (Jumonville 2018; Skene 2019).

Clustering and Hot Spot Detection. There is no common definition of a cluster or hot spot in crime, varying between researchers and sometimes used interchangeably. Eck et al. (2005) identified the common link between definitions as being high concentrations of crime separated by low concentrations of crime. For this study, hot spots are areas of especially dense concentrations of crime, and clusters will refer to the pattern of multiple incidents in a significantly close spatial proximity to each other. This is an important distinction to make, as clusters may exist in less "hot" areas, especially for crime types with a large volume of incidents.

Hot spots can vary in size depending on the study, ranging from hot spot houses to hot spot cities (Harries 1999; Eck et al. 2005). Using clustering and hot spot detection as methods of crime mitigation depends on the assumption that past crime is a reliable indicator for future crime, whether because an area attracts an unusual amount of crime or the area is defined by a particular activity (Levine 2013a). Multitudes of techniques exist in cluster and hot spot analysis, so for the purpose of this review there will be a focus on three techniques: hierarchical, density, and risk-based.

Nearest Neighbor Hierarchical Clustering. Nearest Neighbor Hierarchical Clustering (NNHC) observes the distribution of points in a space to determine where spatial clusters exist, ranging from micro scales (a single building) to macro scales (individual or multiple adjacent neighborhoods). For each cluster, the algorithm identifies the existence of clusters of clusters that then become a second-order of clusters. This continues until all potential clusters are identified (Levine 2013a).

The exploration of crime using NNHC has declined over the past few decades in favor of more quantified methods. The Planning & Organization Directorate of the Kingdom of Bahrain conducted a relatively recent study to identify regional hot spots throughout the country using this clustering method (Singh 2006).

Kernel Density Estimation. Density techniques, particularly Kernel Density Estimation (KDE), identify hot spots by summing the value of all incidents within a space, assessing point event intensity to create a continuous surface within a grid. Greater clustering of events within a grid results in a higher value (Levine 2013a; Levine 2013b).

KDE provides a simple and easy-to-interpret result displaying hot spots identified with defined contours. While useful for displaying hot spots, care must be given towards application in a law enforcement setting as data quality and selection of parameters can affect model results. Kernel density displays risk and there may be no incidents where 'hot' values are estimated (McLafferty et al. 2000).

In KDE literature, researchers may focus on a singular type of crime such as in Liu & Brown (2003) or lump multiple different types of crime together into a single analysis such as in Gerber (2014). The latter shows a lack of consideration about these crimes as a separate phenomenon.

Study Area

The city of Johnson City is situated in the Tri-Cities region of northeast Tennessee with a population of 66,778 (as of a July 2018 Census estimate) and a land area of 111.21 km^2 (as of the 2010 Census) (Figures 2.1-2.2) (United States Census Bureau 2018). The Johnson City Police Department (JCPD) is the main law enforcement agency, servicing the community with 154 sworn officers. The Washington County Sherriff's Office (WCSO), operating out of Jonesborough, also has some jurisdiction in Johnson City. Both JCPD and WCSO subscribe to CrimeMapping, which provides a publicly available map of crime occurrences in their respective jurisdictions.

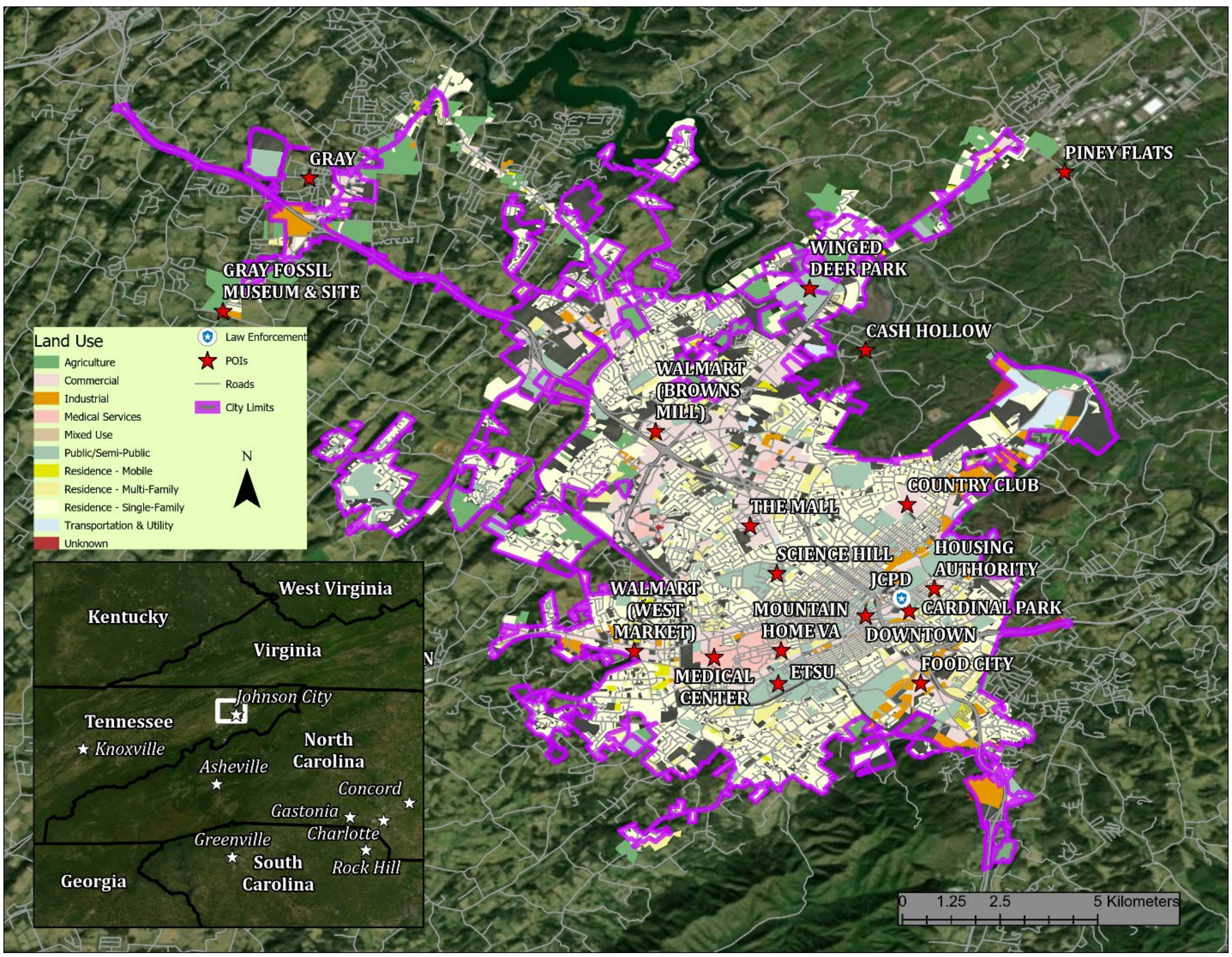

Figure 2.1. Reference map of Johnson City (with labels).

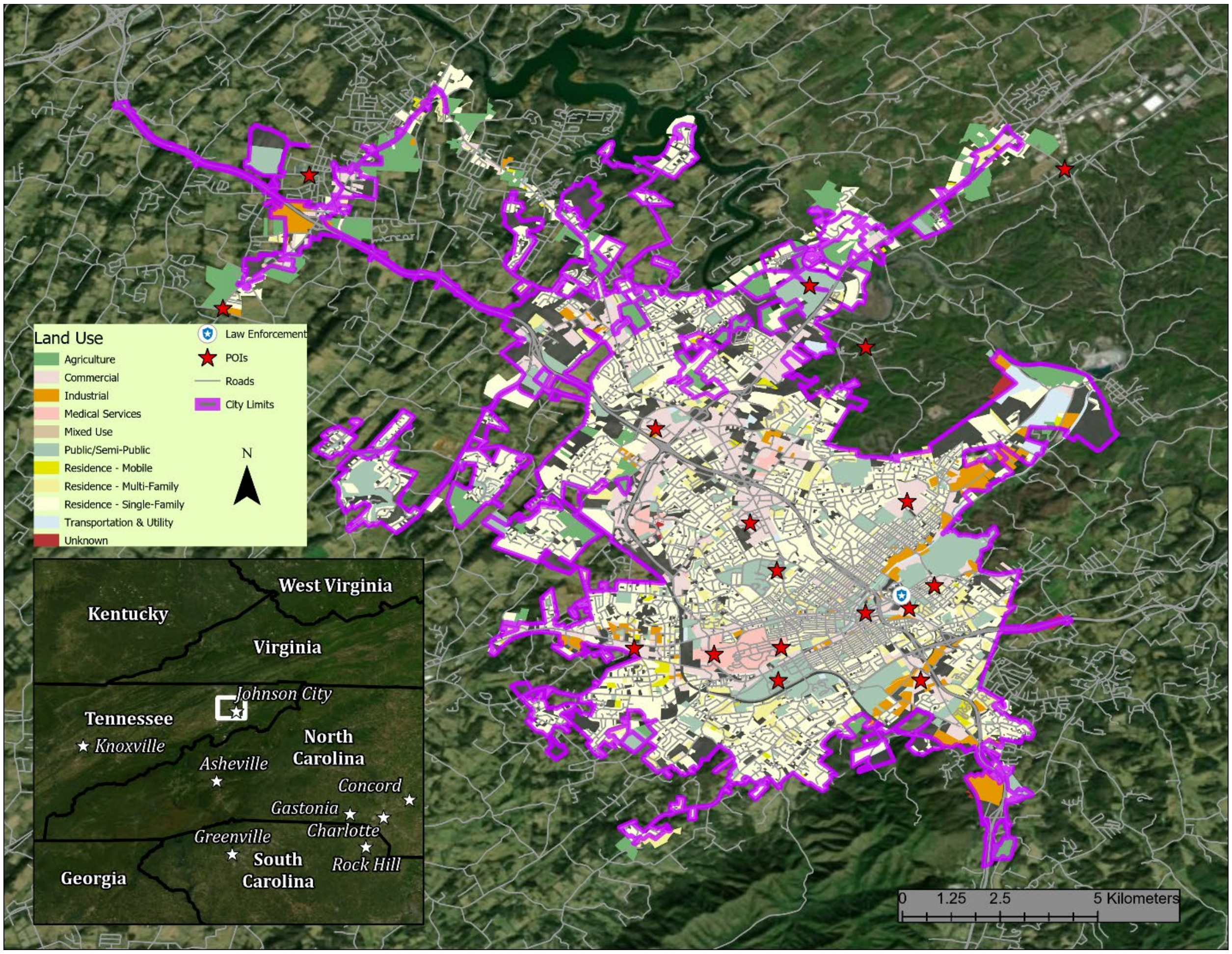

Figure 2.2. Reference map of Johnson City (without labels).

The JCPD publishes annual reports on their website about crime within their jurisdiction to increase public awareness of the goals of the department and to release crime statistics. The 2017 annual report by the JCPD reported a crime index of 4,681 per 100,000 people for "Part I Index" (or Index) crimes. Index crimes include aggravated assault, arson, burglary, larceny, murder, rape, robbery, and vehicle theft. Compared to 2016, murder (50%) and arson (44.4%) saw decreases in 2017 while aggravated assault (2.6%), burglary (19.9%), larceny (18.7%), motor vehicle theft (31.7%), and robbery (22.9%) showed increases. Between 2013 and 2017, there was a slight increase (+1.5%) in *reported* Index crimes, mostly due to a relatively large increase (+18%) in crime in the last year (Johnson City Police Department 2018). That important distinction, that these are only *reported* increases and decreases in crimes, disclaims that these reports may not be a total picture of the true crime in the area. The Department attributes these changes, in part, to greater confidence in the agency's ability to clear cases (Johnson City Police Department 2018). Outside of these rate change calculations, there is currently no implementation of aspatial or spatial statistics in Johnson City crime analysis.

Research Questions

Geostatistical methods may prove to be useful in helping law enforcement identify potential "hot" areas for criminal activity whether it be for crime in general or for a specific type of activity such as larceny or vehicle break-ins. Statistical methods, in general, would help to provide a better understanding of local crime spatial patterns. With that understanding, law enforcement officials can form strategies to mitigate those patterns, reducing crime levels and possibly predicting and planning for future crime trends.

Research Objectives and Questions:

- Examine spatial and temporal patterns in Johnson City crime.
    - Where are clusters and hot spots of crime? Are certain types of crime concentrated in particular areas? Where are these places and why might that be the case?
- Are general theories of where and when crimes typically occur correct in the case of Johnson City (e.g. areas of daily activity, major traffic arteries, etc.)?

Data and Methods

Most data for this study are derived from CrimeMapping (CM), a website developed by TriTech Software Systems to provide the public with information regarding criminal activity.

Local law enforcement agencies subscribe and provide their data to CM, which retrieves and displays new data daily. A map displays each crime incident, indicating the type of crime, a short description of the event, location, and time of the event, and the incident identifier number. Each crime has a generalized address to protect the privacy of parties involved. The description of each crime forms the basis of its categorical assignment in analysis.

CrimeMapping maintains data for each law enforcement agency for a period of up to 180 days. Obtaining a longer-term dataset requires storing the data in a spreadsheet over time or requesting the data from the agency directly. Data collection for this study started in mid-April 2018 and ended in July 2019, allowing a range from 10/15/2017 to 06/30/2019 (624 days) for analysis. During this period, CM data from the JCPD was available for retrieval, but data retrieval from the Washington County Sherriff's Office only started 11/01/2018. To obtain a 2-year dataset, the JCPD fulfilled a request for data from the dates 07/01/2017 – 10/14/2017. To ensure consistency with CM, only crimes that would be reported to CM by the JCPD were retained in analysis. Additionally, no address data were included in the requested data, restricting them to the exploratory section.

As the JCPD's jurisdiction is not explicitly bound to the city limits of Johnson City, and the WCSO holds jurisdiction across the county that Johnson City is only a small portion of, many crime records were removed to focus on criminal incidents around Johnson City proper. To account for boundary effects and Johnson City's irregular border, the convex hull of a 1km buffer of the city limits served as the study extent that all incidents herein lie. Within the study extent over the two-year period 13,288 crimes remained, only 12,041 of which had adequate spatial data. Incidents were separated into types then categories based on their description. Descriptions included the type of violation committed, with slight discrepancies between the

JCPD and WCSO, or were recorded differently despite being the same type of offense (e.g. ROBBERY/INDIVIDUAL vs Individual). Certain crime types are not included in this study due to lacking number of incidents. The decided cutoff is 30 incidents (Table 2.1).

Table 2.1. Summary of crime in JC by categories during study period. Numbers in parentheses include incidents without spatial data.

Type	Category	# of Incidents
Arson†	Arson	17
Assault	Aggravated Assault	319 (363)
	Bomb Threat	4 (5)
	Domestic Violence	6^{α}
	Intimidation	184 (214)
	Simple Assault	1,149‡ (1,310)
	Stalking	37 (41)
Burglary	Forced Entry	74
	Non-Residential Burglary	151 (163)
	Residential Burglary	421‡ (447)
Disturbing the Peace	Bar Disturbance	30
	Disorderly Conduct or Fighting	135 (139)
	Fireworks	5 (8)
Drugs/Alcohol Violations	Drunkenness	795‡ (942)
	Equipment Violation	785‡ (820)
	Liquor Violation	126 (134)
	Liquor, Underage	54 (61)
	Narcotics, Felony	240 (268)
	Narcotics, Misdemeanor	781‡ (894)
	Overdose	64 (71)
DUI	Driving Under the Influence	334 (388)
Fraud	Credit Card/ATM	345‡ (375)
	Counterfeiting & Worthless Checks*	2
	Embezzlement*	1
	False Pretenses, Swindling, etc.	495‡
	Identity Theft*	8
	Impersonation	139 (155)
	Phone Prescription	8
	Theft of Services	2
	Wire & Electronic	16
Homicide*†	Murder and Non-Negligent Manslaughter	1
Motor Vehicle Theft	Multiple	416 (442)
Robbery	Business	11 (13)
	Individual	65 (73)
Sex Crimes*†	Obscene Material	1

	Sexual Assault	8
	Other (Incest, Sodomy, etc.)	0
Theft/Larceny	Bicycle	79 (82)
	From Building	638‡ (710)
	From Coin Machine	5
	From Yard	230 (239)
	Fuel	8 (9)
	Mail or Delivery	62 (64)
	Motor Vehicle Parts or Accessories	265 (275)
	Pick-pocketing & Purse-snatching	12
	Possession of Stolen Property	2 (3)
	Shoplifting, Felony	41 (46)
	Shoplifting, Misdemeanor	1,570‡ (1,793)
	Trailer	35 (36)
	All Other	186 (194)
Vandalism	Destruction of Private Property	48
	Felony	151 (159)
	Misdemeanor	604‡ (643)
	Other Property Damage	0 (16)
Vehicle Break-In	From Motor Vehicle	716 (772)
Weapon	Explosives Pickup	8 (11)
	Other Weapon Violations	158 (182)

* Data solely comes from the Washington County Sherriff's Office.
† Denotes data excluded from analysis due to lacking sufficient incidents (30).
‡ Denotes a top ten category for further analysis.
α Data were split between aggravated (4) and simple assault (2) for analysis based on original CM description.

Exploratory Methods

Histograms of crimes by type and category over days and minutes can give a picture of short-term temporal patterns in local crime. For all crime and crime type (when included), four temporal histograms measuring counts of incidents throughout the study period, each month in the year, each day of the week, and each hour in a day were created using the Statistical Package for the Social Sciences (SPSS) version 25. Hourly histograms are binned for approximately every 30 minutes, while histograms over the study period are binned for around 10 days (~3 bars per month). Days of the week and months are in order according to the calendar (e.g., 1 for Sunday or 1 for January).

SPSS contains multiple analyses to test the significance of trends found and differences between groups of time (e.g. day vs. night, weekday vs. weekend). For this, the linear regression and poisson generalized linear model will be used to determine the significance for trends of crime through the study period. To determine significance within the other temporal trends (month, day, and hour), other statistical tests work better due to the potential nonlinearity of those trends (e.g. seasonal variation between months, day/night). The Mann-Whitney (MW) and Kruskall-Wallis (KW) tests, while not as powerful as T tests or ANOVAs, account for nonparametric data distributions by automatically ranking the data. Tests comparing two groups use MW while tests of three or greater use KW (Reed College n.d.). Months are broken down between the astronomical and meteorological seasons, and additionally between when school is in session at East Tennessee State University. Days of the week are split between the weekday and weekend. Lastly, hours of the day are separated by daylight and nighttime hours (i.e. 6am – 6pm).

Analytical Methods

This study looks to calculate clusters and hot spots of each type of crime that surpassed the 30-offense threshold and the ten most common categories of crime through NNHC and KDE. Each occurrence served as the input for NNHC & KDE in CrimeStat IV. The reference grid and measurement parameters are based on the maximum spatial extent of crime incidents throughout the study period.

For risk-adjusted analyses, the Oak Ridge National Lab LandScan Global Population dataset provided ambient daytime population to adjust hot spots according to the average population an area maintains in a 24-hour period (Oak Ridge National Laboratory 2017).

Nearest Neighbor Hierarchical Clustering (NNHC). The NNHC method, known within CrimeStat IV as "Nearest Neighbor Hierarchical Spatial Cluster (Nnh)", is one of the older methods of cluster analysis. CrimeStat IV uses a unique algorithm with a defined "threshold distance" between individual pairs of points to determine cluster suitability, one of three important parameters. Users can manually define this distance or allow CrimeStat to calculate the distance by the following equation, where A is the area of the study extent and n is the number of incidents:

$$d_{NN(ran)} = 0.5\sqrt{\frac{A}{n}}$$

Further, search radius (or confidence interval) assigns a probability to the distance between points based on a chance distribution. Lastly, minimum points per cluster (MPPC) is a self-explanatory parameter, determining how many points need to fit together to create a cluster of any order (Levine 2013a).

Choosing random threshold distance reduces the subjectivity of clusters. For confidence interval of the search radius, a value of 0.01 (fourth from left on the CrimeStat scale) indicates a 1% chance of assigning points to a cluster based on a chance distribution. That leaves MPPC, the only subjective parameter in this case. Minimum points will vary depending on the n value of the type/category:

- If $n > 1{,}000$, MPPC = 1% of n
- If $n > 100$, MPPC = 10% of n
- If $n > 30$, MPPC = 20% of n
- If the above methods fail to generate clusters, halve the value. Failing that divide the original value by three, and so on until achieving sufficient clustering.

Kernel Density Estimation (KDE). Changes in interpolation method, grid cell size, and bandwidth have different levels of importance in relation to the accuracy of KDE surfaces. In his study of Newcastle-upon-Tyne assaults and residential burglaries, Chainey (2013) states cell size has little effect on a kernel density surface, adding that bandwidths require special consideration and that smaller bandwidths lead to better predictive results. This is a valid thought considering larger bandwidths can lead to overly smooth surfaces. Hart and Zandbergen (2014) agreed on both these matters, placing little importance on grid cell size and highly recommending smaller bandwidths. They added that choice of interpolation method has a significant effect on accuracy, showing triangular and quartic as accurate predictors compared to normal and uniform, which underperformed (Hart and Zandbergen 2014). Some statisticians contend that most interpolation methods have hardly any important distinctions outside of determining smoothness (Vermeesch 2012). Interpolation methods weigh points within a specified bandwidth based on their function/shape. CrimeStat contains five interpolation functions: normal, negative exponential, quartic, triangular, and uniform. Normal interpolation, the most common, has a bell curve shape extending endlessly through every location in a study extent, unlike the other functions in CrimeStat. Negative exponential kernels exhibit drastic drops in density with distance from the kernel center. Quartic functions have a more gradual falloff until the end of the bandwidth. A triangular bandwidth loses weight in a linear relationship with distance. Lastly, in a uniform function all points within the bandwidth weigh the same (Levine 2013b).

Single kernel density and dual kernel density methods measure kernel density for raw hot spots and risk-adjusted hot spots for Johnson City crime respectively. The interpolation method chosen for a type or category depends on the spatial distribution of the crime and its frequency. Quartic shape for more spatially concentrated crimes, and triangular for more widely distributed crimes, were the only implemented shapes given their acceptance relative to other methods. Kernel bandwidth varies across crime types and categories based on their number of incidents and standard distance deviation using the Silverman equation as follows where n is the number of incidents and σ is the standard distance deviation of incidents (Tables 2.2-2.3):

$$\boldsymbol{h_0 = (\frac{4\sigma^5}{3n})^{\frac{1}{5}} \approx 1.06\sigma n^{-\frac{1}{5}}}$$

Table 2.2. Summary of kernel parameters for each eligible crime type.

Type	Interpolation Method	h_0	MPPC
All Crime	Quartic	0.685	120
Assault	Quartic	1.071	17
Burglary	Quartic	1.333	16
Disturbing the Peace	Triangular	1.260	9
Drugs/Alcohol Violations	Quartic	0.843	28
DUI	Triangular	1.347	11
Fraud	Quartic	1.137	10
Motor Vehicle Theft	Triangular	1.565	14
Robbery	Triangular	1.676	8
Theft/Larceny	Quartic	0.826	31
Vandalism	Triangular	1.255	20
Vehicle Break-In	Quartic	1.324	18
Weapon	Triangular	1.504	8

Table 2.3. Summary of kernel parameters for the top ten categories.

Category	In. Method	h_0	MPPC
Credit Card/ATM Fraud	Triangular	1.521	17
Drug Equipment Violation	Quartic	1.162	26
Drunkenness	Quartic	0.940	27
False Pretenses, Swindling, etc.	Quartic	1.193	17
Misdemeanor Narcotics	Quartic	1.181	26
Misdemeanor Shoplifting	Quartic	0.774	16
Misdemeanor Vandalism	Quartic	1.106	15
Residential Burglary	Quartic	1.196	14
Simple Assault	Quartic	1.196	11
Theft From Building	Quartic	1.110	21

Results

Exploratory Analysis

All Crime. Through temporal analysis, crime in Johnson City increased from the latter half of 2017 into 2018, and fluctuated in subsequent months. Between all crimes (month over month), there is a dip in crime going into the summer before rising again into autumn. A similar, albeit smaller, trend exists with winter. Between days of the week, trends are much slighter with a falloff of crime during the weekend and Wednesday. Crime generally seems to peak in the daylight hours, increasing with dawn and decreasing with dusk. Especially noteworthy is the freefall of crime after 6pm (1800) and rebound an hour later (Figure 2.3). Regression analyses report a significant, increasing, trend (0.000) in crime across the study period. Differences between astronomical seasons (Jan, Feb, Mar for Winter, etc.) are additionally significant (0.45), however the meteorological and school seasons are not. Neither the day of the week or time of day have trends holding significance.

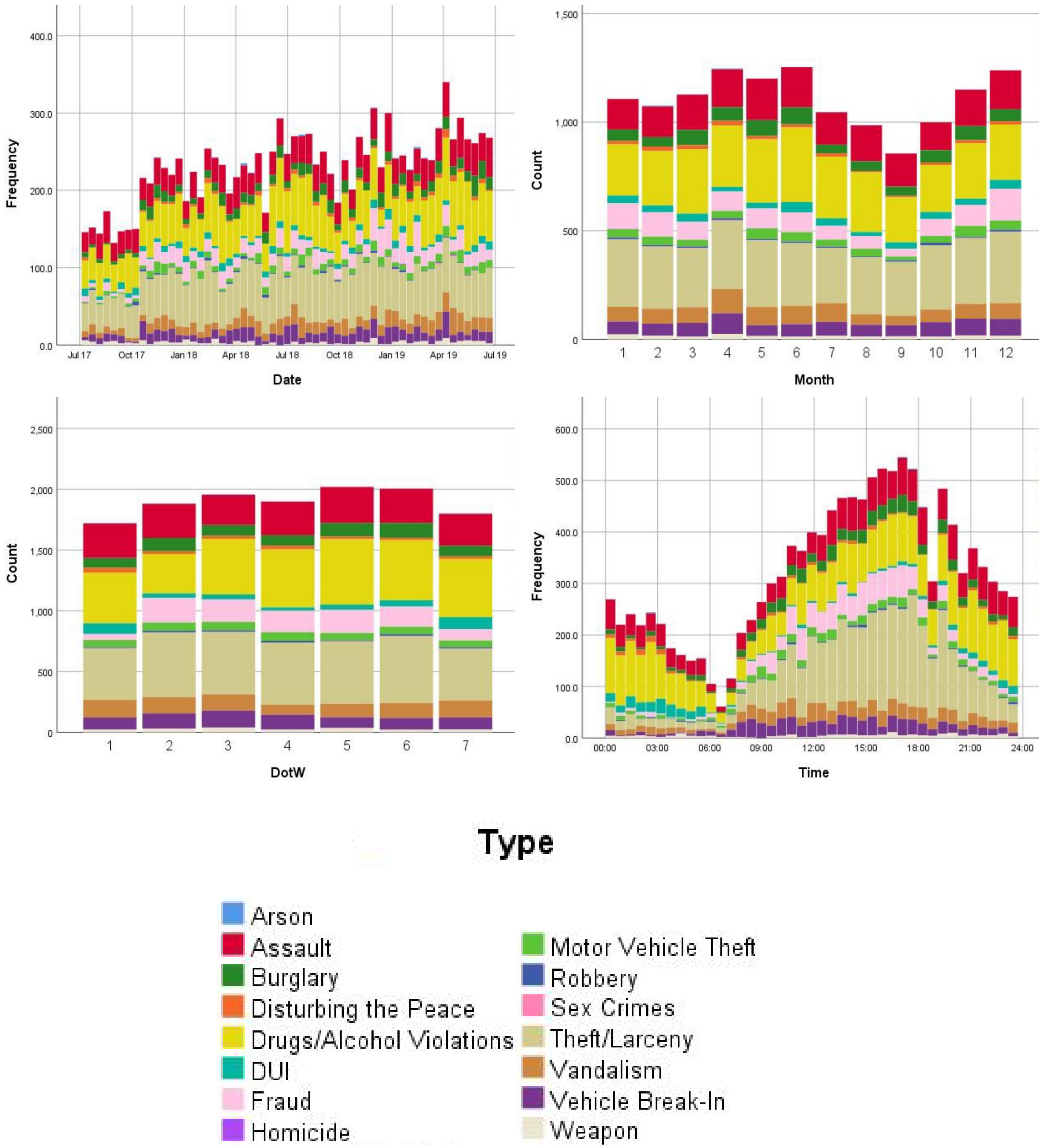

Figure 2.3. Histograms showing all crime during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Assault. Assaults continuously fluctuated throughout the study period. With months, assault trends are comparable to all crimes, elevated in the spring and less common in the summer. Somewhat the same can be said of hours in the day as offenses begin to increase at dawn but increase quickly after lunch, only to fall later in the evening (Figure 2.4). Despite fluctuation, the trend of crime over the study period is positive and significant (0.000).

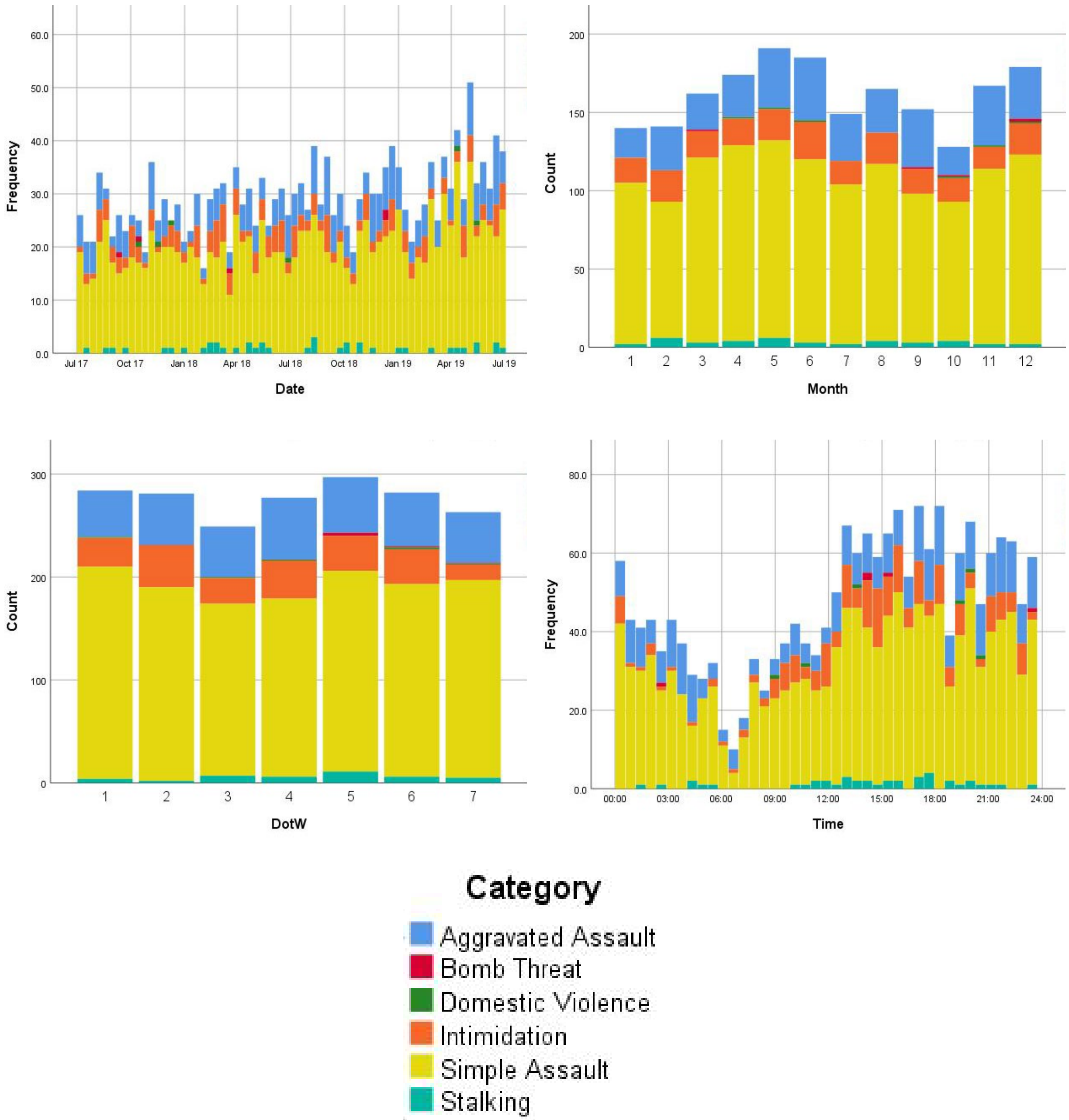

Figure 2.4. Histograms showing assaults during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Burglaries. Both period and monthly histograms showed surges and declines in offenses between months, with the height of offenses occurring in the spring and drastic decline in the summer. More burglaries occurred on weekdays, notably during hours correlating with a typical work schedule, with some fluctuation (Figure 2.5). Burglary additionally tests positive for a significant and increasing trend for crime across the study period (0.000). Burglary produced additional significant trends with astronomical seasons (0.024) and time of day (0.005).

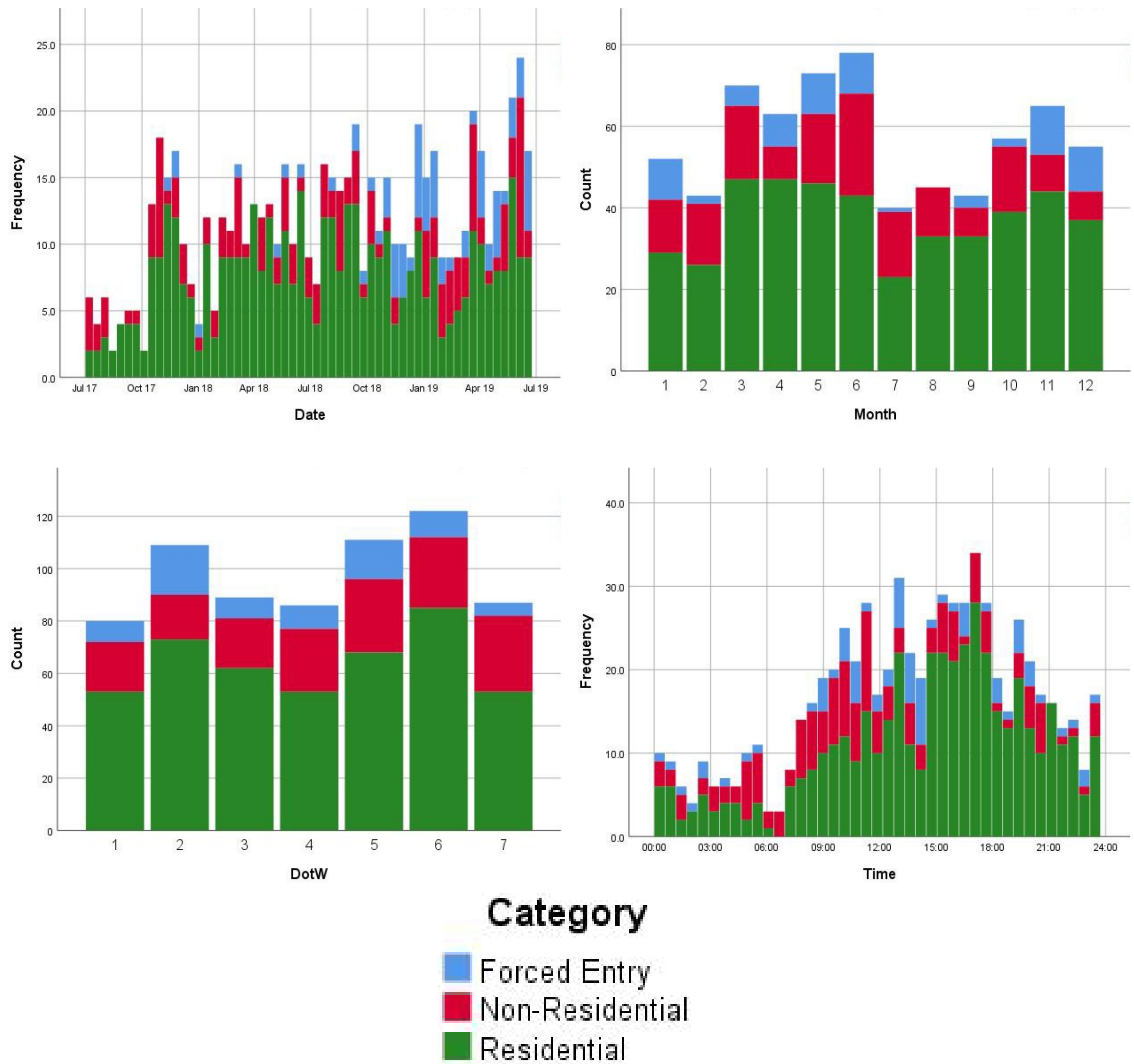

Figure 2.5. Histograms showing burglaries during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Disturbances of the Peace. One of the scarcer crime types in these analyses, there is typically no more than five or six incidents of the peace being breached in any 10-day period. The first half of April 2019, however, saw more than double the usual number of offenses. In months, a drop in disturbances occurred in the late summer then steadily increased until reaching a peak between mid-winter and the beginning of spring.

Bar disturbances were an outlier when observing disturbances by day of the week and hour of the day, with a relatively high concentration of occurrences on Sundays. Bar disturbances solely occurred during the late night hours and make these times the peak for this crime type, making it one of the only crime types to see an *increase* after dusk. After bars and similar businesses close for the night, disturbances plummet until day arrives and the overlying trend of crime increasing during daylight hours and decreasing in the evening resumed (Figure 2.6). The significance of disturbance of the peace data shows in the analysis of the study period (0.000) and the astronomical seasons (0.032).

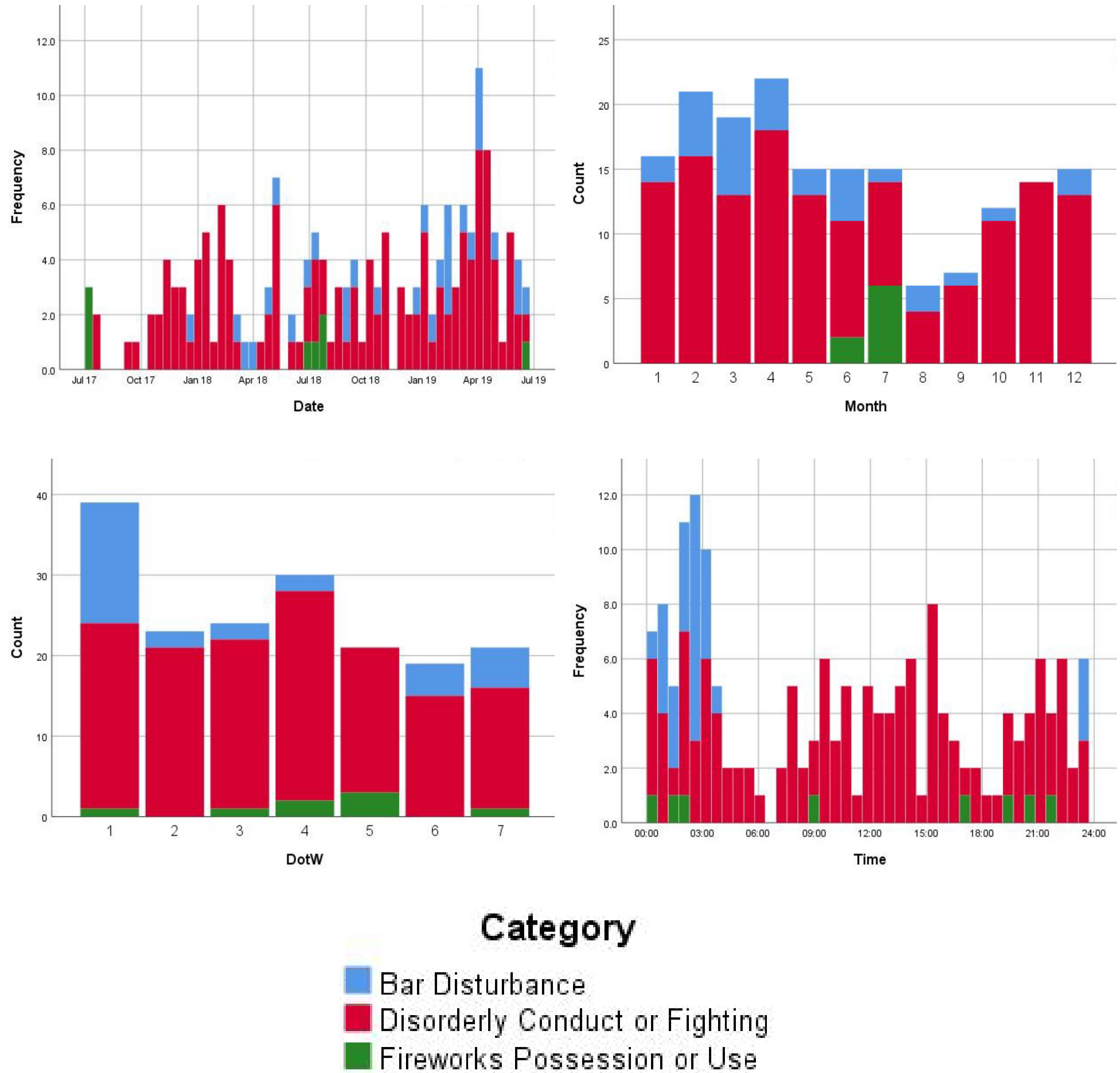

Figure 2.6. Histograms showing disturbances of the peace during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Drugs & Alcohol. Over the study period, the occurrence of drug offenses fluctuated frequently but tended to stay relatively level. Hourly, drug offenses peak at night, not beginning to fall off until around 3am until increasing again at around 7am (Figure 2.7). Analyses over the study period (0.000), meteorological seasons (0.041), and day/night (0.020) successfully tested the significance of variation between temporal data.

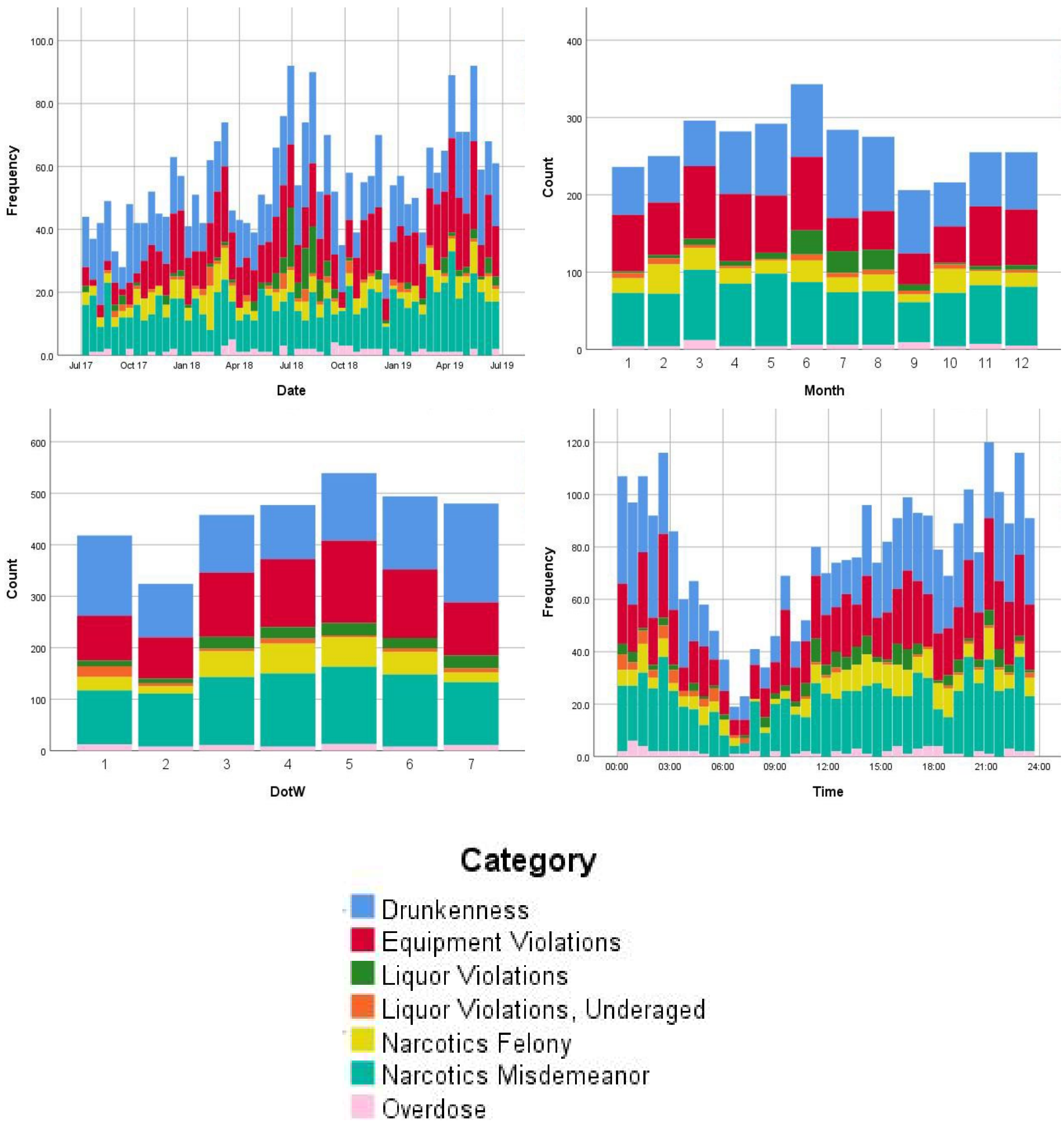

Figure 2.7. Histograms showing drug & alcohol violations during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

DUIs. Unlike the all crimes dataset and most other crimes, DUIs over the study period have stayed at around the same level with some drops and rises from time to time. Wintry months largely have higher cases of DUIs with the exception of June. Clear temporal patterns in DUIs exist in the weekends and after dusk hours as people leave work, go to the bar, or party (Figure 2.8). The linear and poisson regression analyses produced slightly different, but still significant, values (0.016 and 0.012 respectively). The hour of the day trend is also a significant trend among the DUI data (0.000).

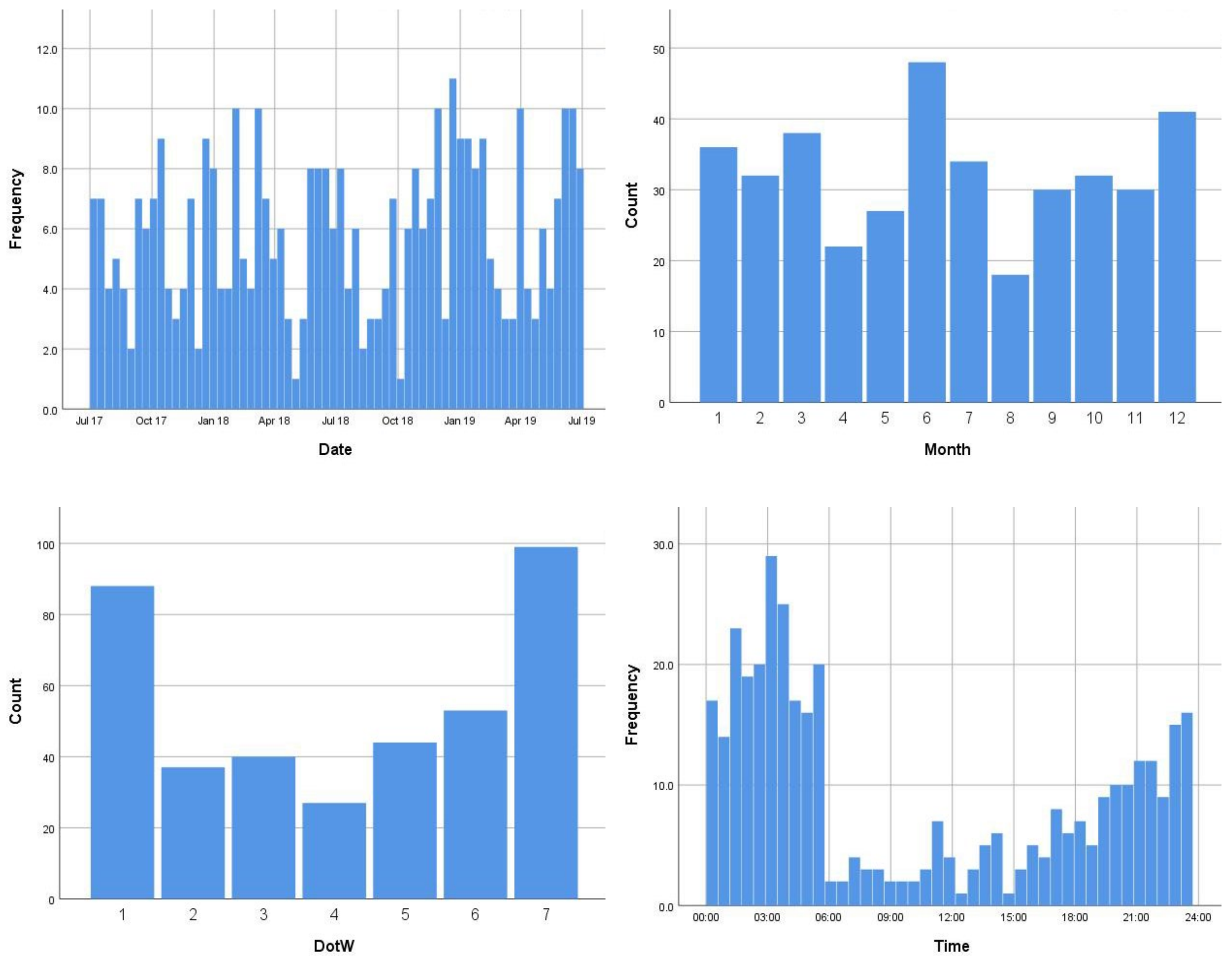

Figure 2.8. Histograms showing DUIs during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Fraud. Like all crimes, fraud through the study period began relatively low and increased after October. An unusual spike occurred in credit card/ATM fraud December 2018 and February 2019 before stabilizing. There was a clear trend of fraud occurrences during the workday, with cases of false pretenses and impersonation primarily comprising the nighttime and weekend occurrences of fraud (Figure 2.9). Fraud over time holds statistical significance with a positive trend (0.000). Hour of the day comes out as a significant difference between data groups (0.000).

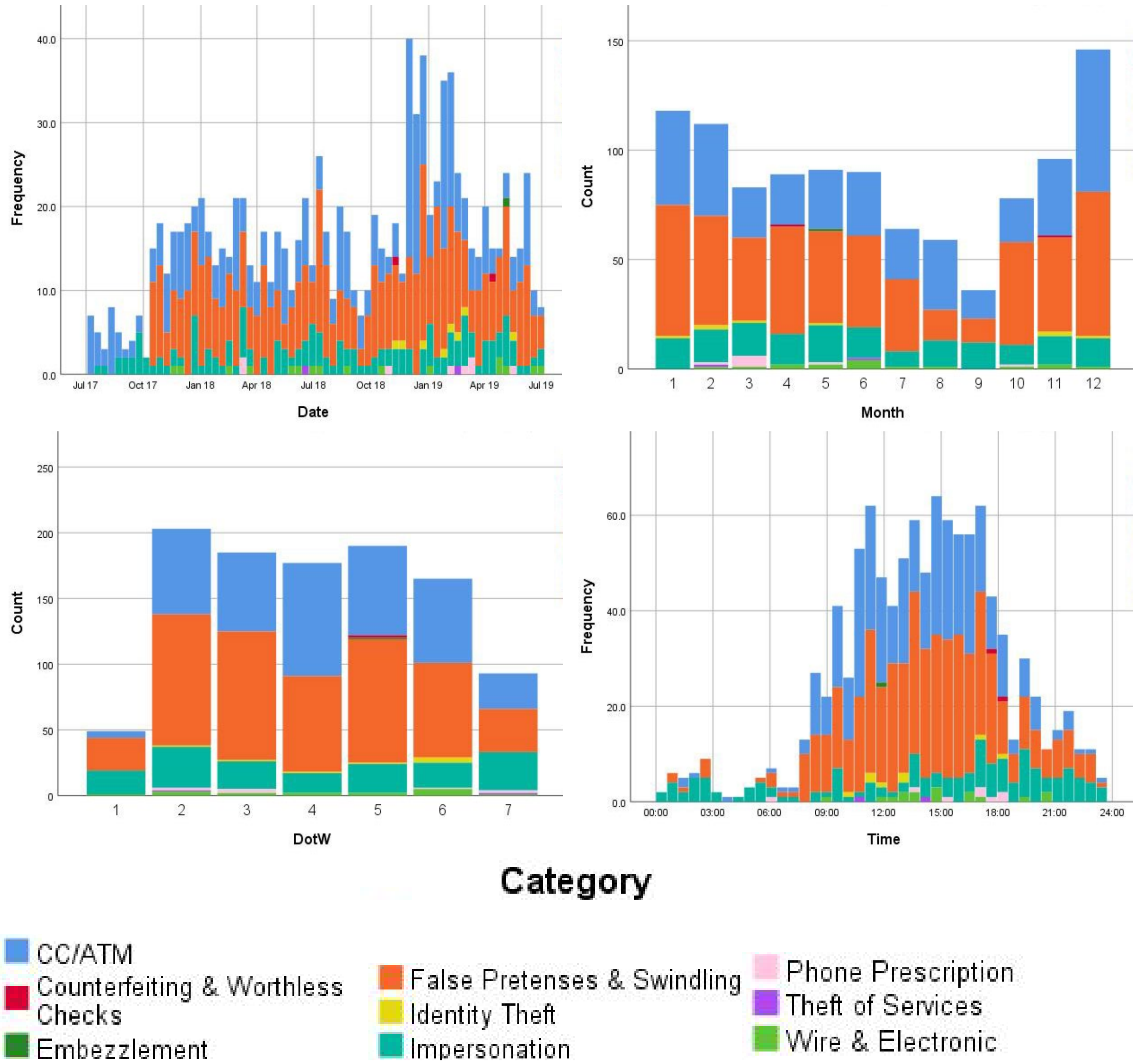

Figure 2.9. Histograms showing fraud during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Motor Vehicle Theft. This crime type also exhibits surging crime after October 2017 however numbers decline to previous levels in subsequent months, fluctuating over time. Between months, September experienced the lowest occurrence of vehicle thefts with November having the peak occurrences. Again, this crime type more-or-less follows the same hourly trend with all crime, increasing at dawn and decreasing at dusk (Figure 2.10). The occurrence of motor vehicle thefts over time is increasing with statistical significance (0.000). Hour of the day, again, comes out as having significant variations between day and night (0.000).

Figure 2.10. Histograms showing motor vehicle thefts during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Robberies. Being the crime type with the fewest instances, there was typically no more than three occurrences of robbery in any 10-day period. However, the beginning of October 2017 saw a surge in robberies with greater than double the usual number of robberies seen in a 10-day interval. The month of October and, slightly, the day of Friday experienced the most robberies. Peak time for robberies occurred around 3pm (Figure 2.11). No significant trends were observed within robbery data.

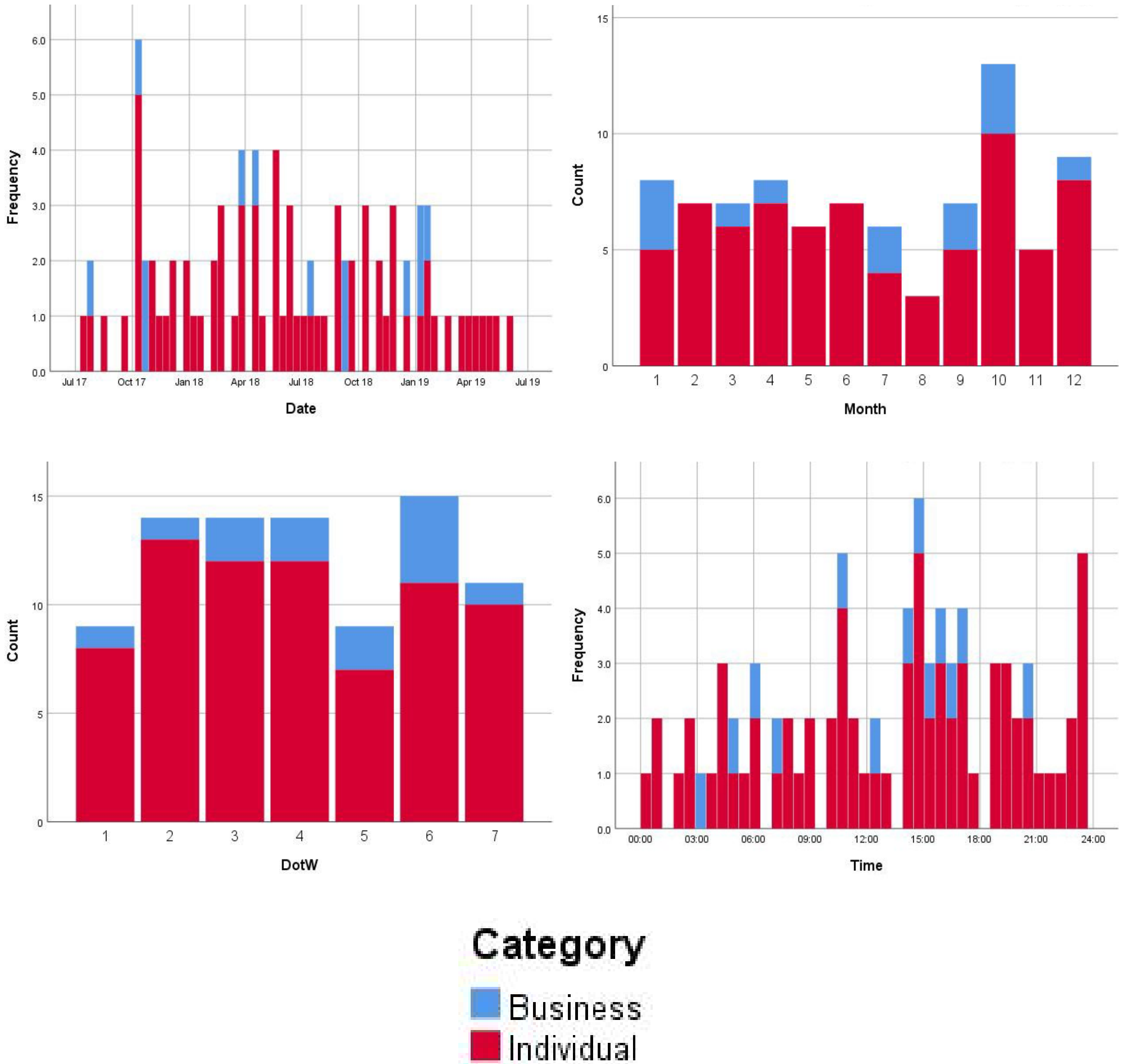

Figure 2.11. Histograms showing robberies during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Thefts. The typical jump in crime in October 2017 was not as jarring in the thefts histogram. Between months, there were small increases and decreases, with December holding the most offenses by a relatively slight number. The same can be said with weekdays, though weekends showed a significant decrease. Hourly, thefts focused mostly in the daylight hours starting around 8am and slowing after 7pm (Figure 2.12). For the study period, there is a significant increase in the occurrence of theft (0.000). The difference between the day and night trends were significant (0.039).

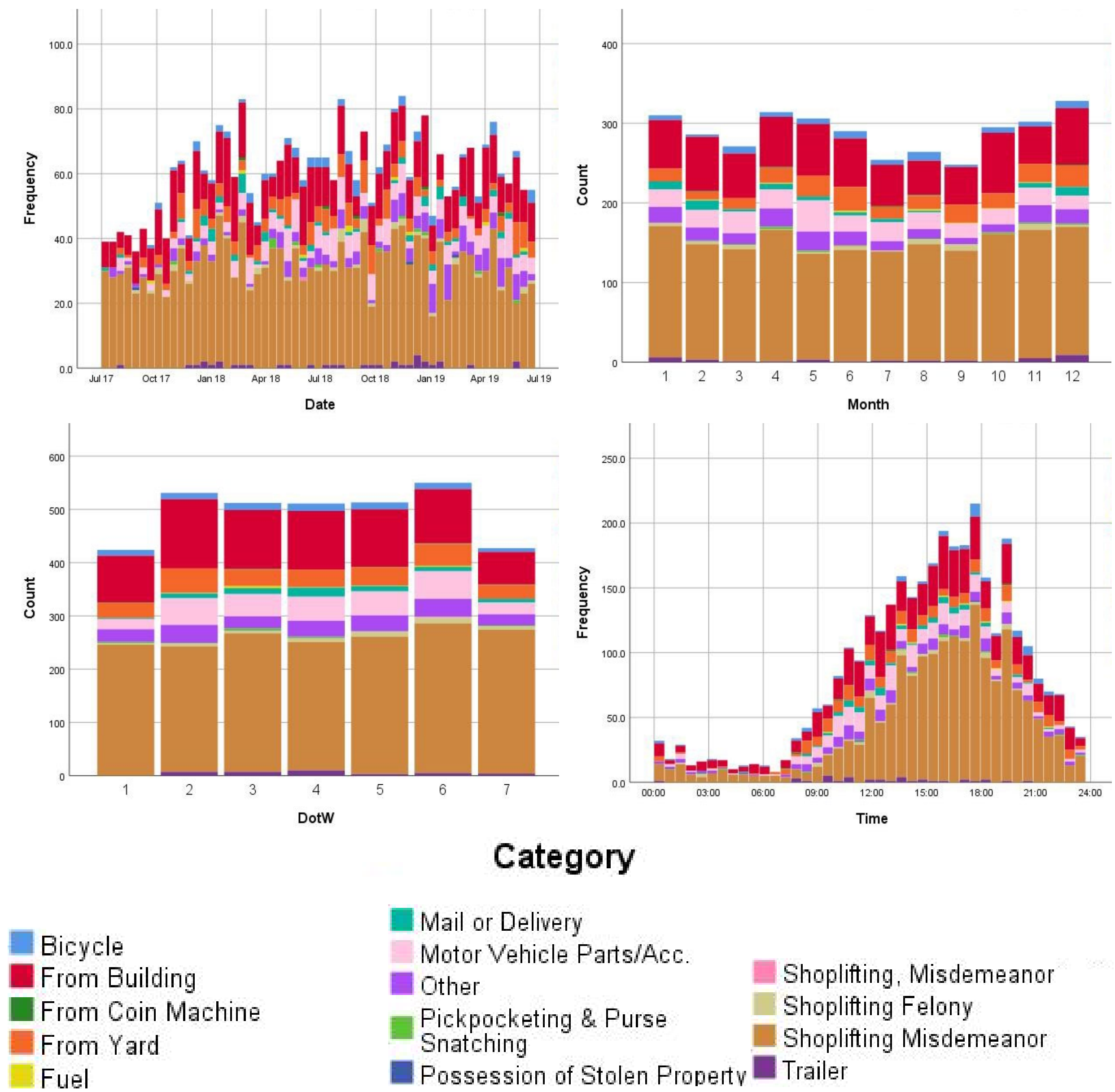

Figure 2.12. Histograms showing thefts during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Vandalism. The occurrence of vandalism in Johnson City exhibited a slight, but steady, increase with occasional spikes. Vandalism peaked in the month of April, decreasing through to the end of summer then increasing in the latter part of the year. Weekends are the height of vandalism occurrence, with Wednesday marking the lowest point. Vandalism is another crime that has an hourly trend correlating with the presence of daylight, with a sudden drop in offenses shortly before noon (Figure 2.13). Again, regression analyses calculate that the increasing trend of vandalism is significant (0.000). The day and night difference in vandalism data also comes out as statistically significant (0.006).

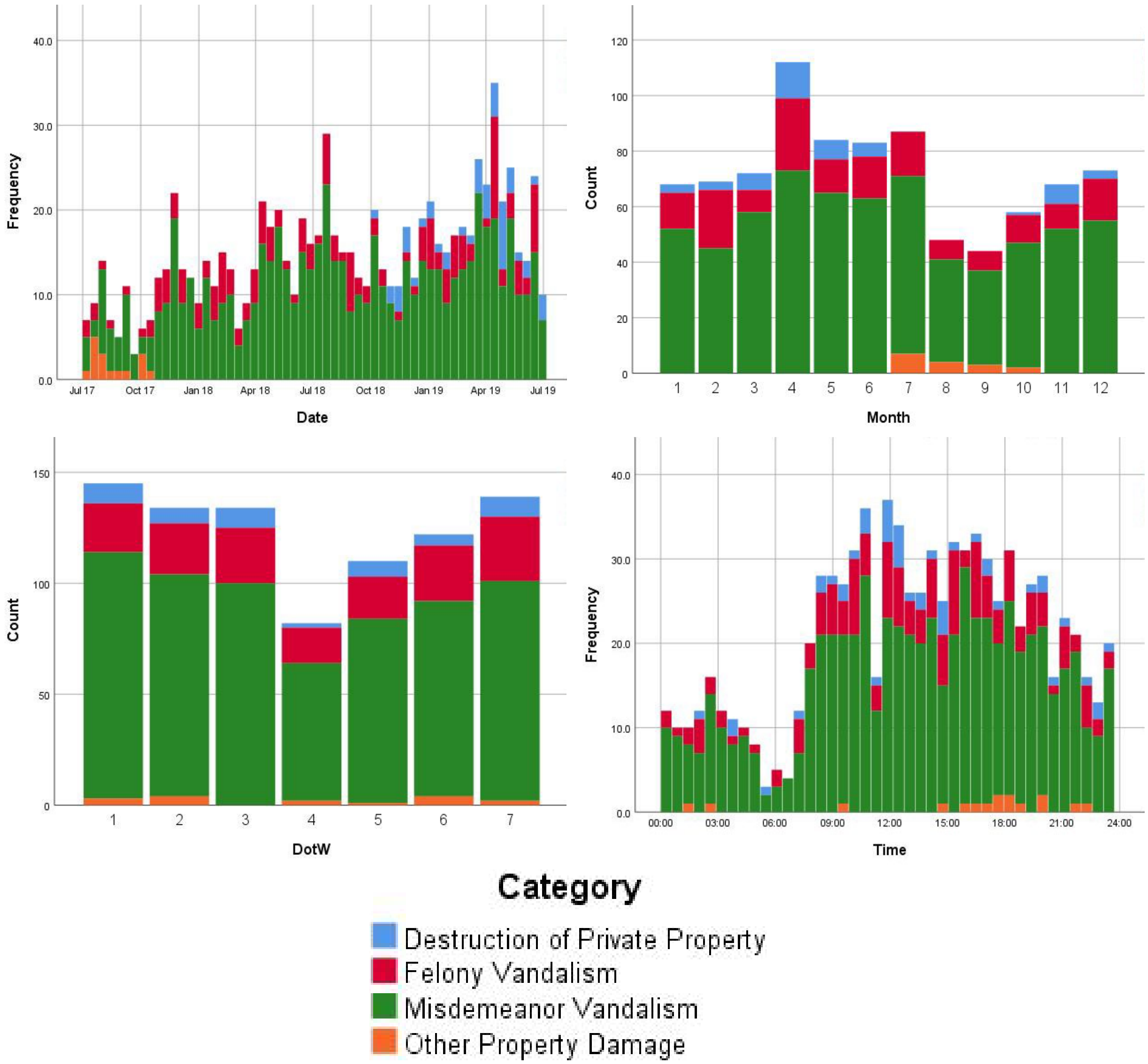

Figure 2.13. Histograms showing vandalism during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Vehicle Break-Ins. By month, April has a higher count of vehicle break-ins, with May following with the lowest count. The highest and lowest occurrence of vehicle break-ins occur during weekdays, Tuesday and Thursday respectively, but still appear to be a workday-focused crime type. In regards to hours, vehicle break-ins also follow the trend of increasing during dawn and decreasing closer to dusk (Figure 2.14). Vehicle break-in data produced a significant trend for the study period (0.000) and day against night (0.000).

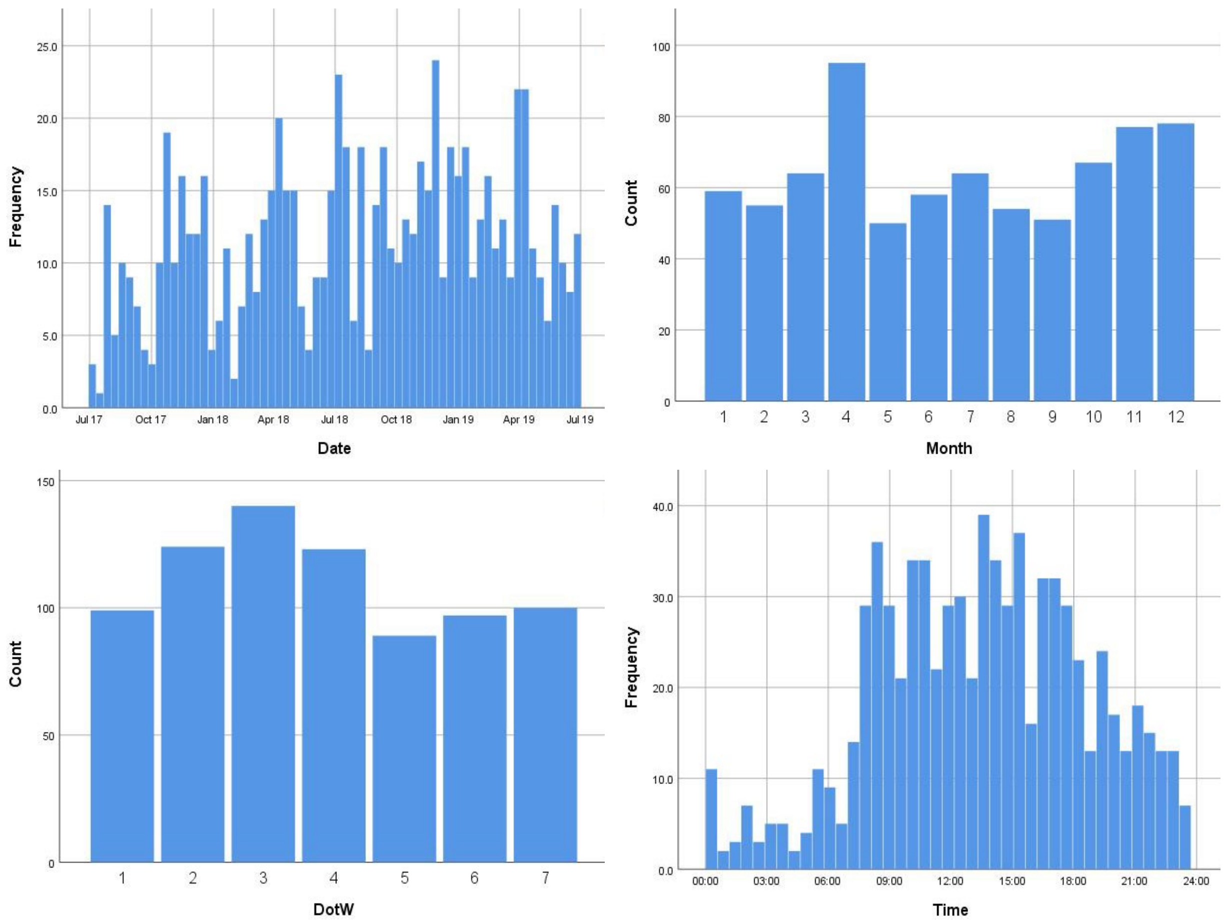

Figure 2.14. Histograms showing vehicle break-ins during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Weapons. Over the study period, weapon offenses did not see much fluctuation. Over months April has the highest amount of weapon violation occurrences, although there does not seem to be a favored season. The hourly histogram of weapon offenses does not have as pronounced a trend as other histograms, showing maybe slight favor for daytime offenses (Figure 2.15). No trends in weapon offense data produced a significant effect.

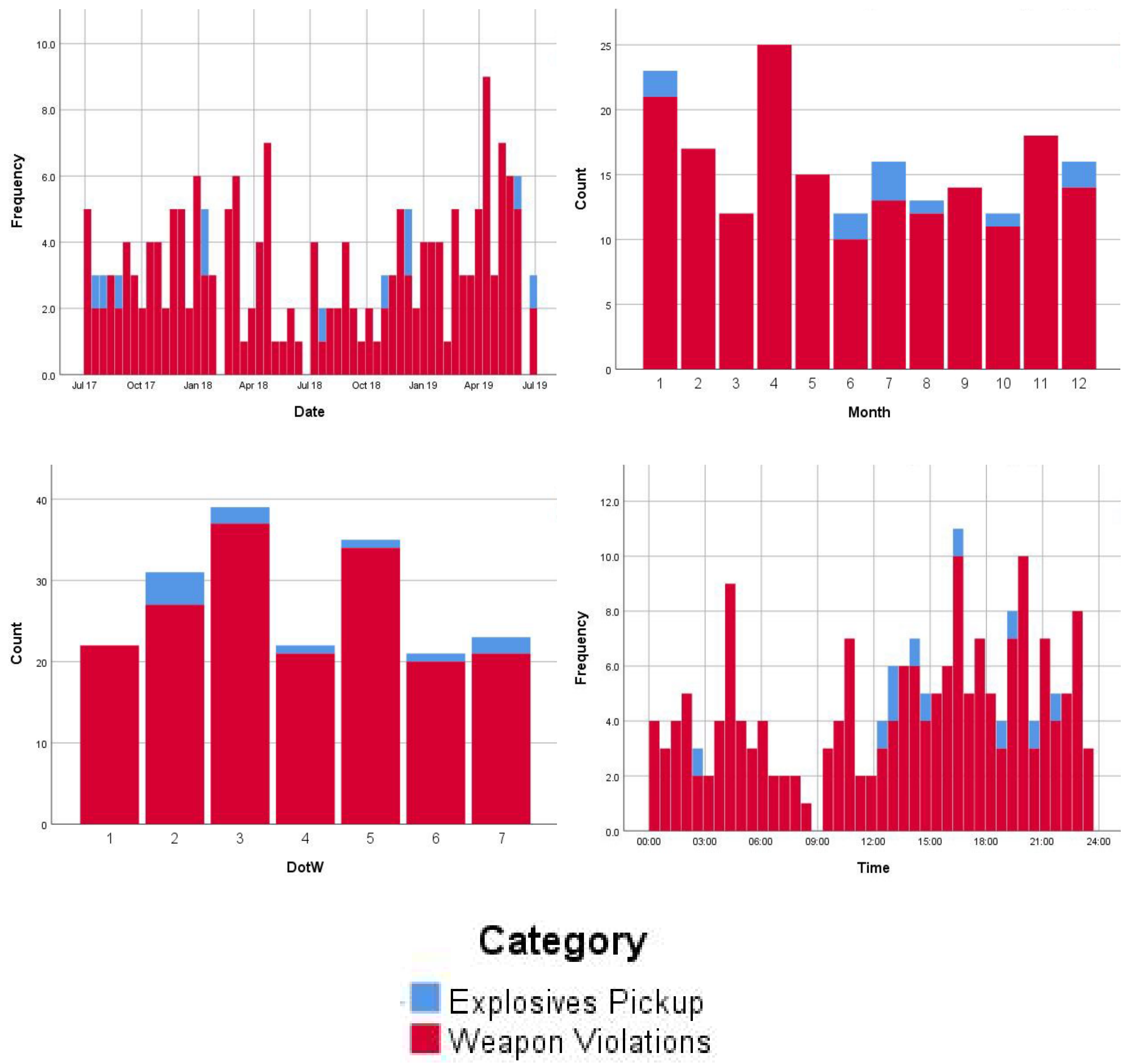

Figure 2.15. Histograms showing weapon offenses during the study period (a), over months of the year (b), over days of the week (c), and over hours in the day (d).

Clusters and Hot Spots

Maps for each crime type displayed the resulting kernel density surfaces and hierarchical clusters from crime incidence points. Most bandwidths calculated by the Silverman method created large and overly smooth raw crime surfaces and minute risk-adjusted surfaces. Halving the bandwidth produced better raw surfaces, while for risk-adjusted surfaces a quarter of the bandwidth (1.25%) to the final bandwidth produced easier surfaces to interpret. Due to this change, some hot spots partitioned into relatively massive areas of high density.

Notable clustering and highly dense concentrations of these broader crime types appeared in numerous areas of interest. Normal cluster and hot spot methods generally matched with each other. Downtown, the Mall, and Walmarts (on both West Market Street and Browns Mill Road) consistently appeared as 'neighborhoods' of high crime density and clustering. Interesting results came out of adjusting for average daily population trends. Most downtown hot spots contracted significantly but still represented relatively high areas of crime, while the two Walmarts were relatively preserved as areas of high crime. Many new hot spots emerged in the periphery of Johnson City, especially in the Cash Hollow area (Tables 2.4-2.6, Figures 2.16–2.28).

Table 2.4. Summary of areas with clustering and hot spots of crime by type.

Crime Type	Hierarchical Clustering	Kernel Density
All Crime	Downtown, Mall, Med Center, Walmarts	
Assault	Downtown, Science Hill, housing around Founders park, housing around industrial areas and other low-income areas	
Burglary	Downtown, areas of low income and multi-family housing.	
Disturbing the Peace	Downtown, Mall, Medical Center, Science Hill	Downtown, Science Hill
Drugs & Alcohol	Budget motels, ETSU/Tree Streets, Downtown, Walmarts	Downtown, Walmarts
DUI	Downtown, ETSU, Mall	
Fraud	Mall, Medical Center, Mountain Home, Walmarts, various other commercial and low-income areas.	Mall, Medical Center, Walmarts
Motor Vehicle Theft	Downtown, low income housing	H-321, Bristol Hwy, Downtown, low income housing, Medical Center
Robbery	Downtown	Commercial area north of Med Center, Downtown
Theft/Larceny	Downtown, Food City, Mall, Medical Center, Walmarts,	Downtown, Food City, Mall, Medical Center, Tree Streets,

		Walmarts, low-income housing
Vandalism	Downtown, low-income housing	
Vehicle Break-In	Downtown, low-income housing, housing SW of ETSU	
Weapon	Downtown, Mall commercial area, Science Hill, Walmart (H-321)	

Table 2.5. Summary of areas with risk-adjusted clustering and hot spots of crime by type.

Crime Type	Hierarchical Clustering	Kernel Density
All Crime	Downtown, Mall, Med Center, Walmart’s	Cash Hollow area
Assault	Downtown, Mall, Medical Center, Science Hill, commercial and residential areas around campus	Cash Hollow area, industrial and low-income area residences
Burglary	No clusters generated.	Cash Hollow, industrial area, housing/commercial towards Jonesborough
Disturbing the Peace	No clusters generated.	Between Downtown and Science Hill.
Drugs & Alcohol	Downtown, Target, Walmarts	
DUI	No clusters generated.	H-321 to Jonesborough, Downtown, Tree Streets
Fraud	Mall, Medical Center, Walmarts	Bristol Hwy to Piney Flats, Mall, Walmart’s
Motor Vehicle Theft	No clusters generated.	H-321 to Jonesborough, Bristol Hwy, east industrial area, low-income housing
Robbery	No clusters generated.	Cash Hollow, Downtown
Theft/Larceny	Food City, Mall, Med Center, Walmarts	Cash Hollow, Food City, Mall, Walmarts
Vandalism	No clusters generated.	Yes.
Vehicle Break-In	Downtown	Downtown, Housing around industrial areas, housing SW of ETSU
Weapon	No clusters generated.	Cash Hollow, H-321 to Jonesborough

Table 2.6. Legend of cluster and KDE maps.

Nearest Neighbor Hierarchical Clustering		**Kernel Density Estimation**	
	1st Order Clusters (White)		Low Density
	2nd Order Clusters		Moderate Density
	3rd Order Clusters		High Density

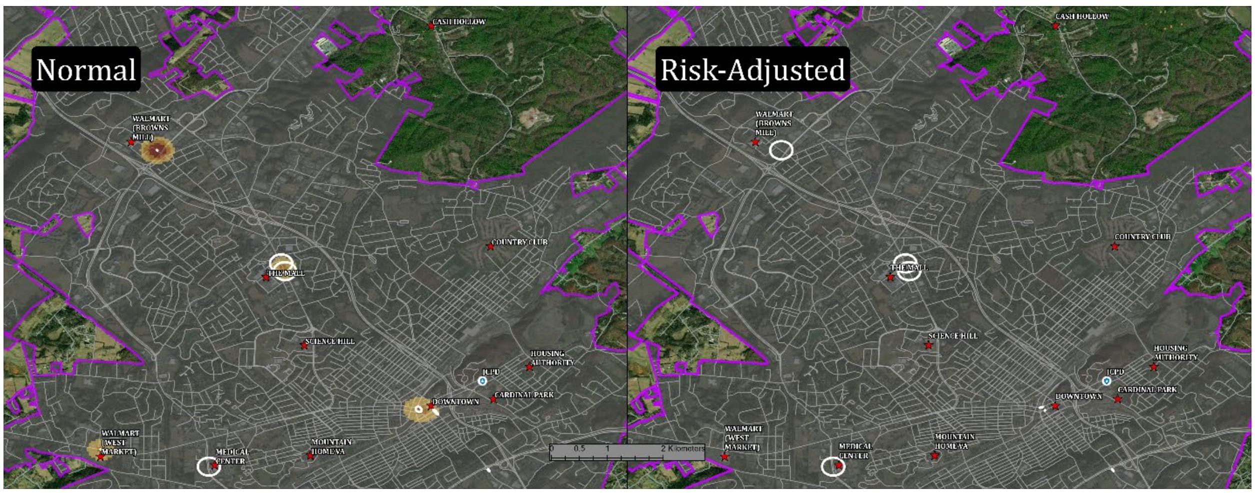

Figure 2.16. Clusters and KDE surfaces for all crimes in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

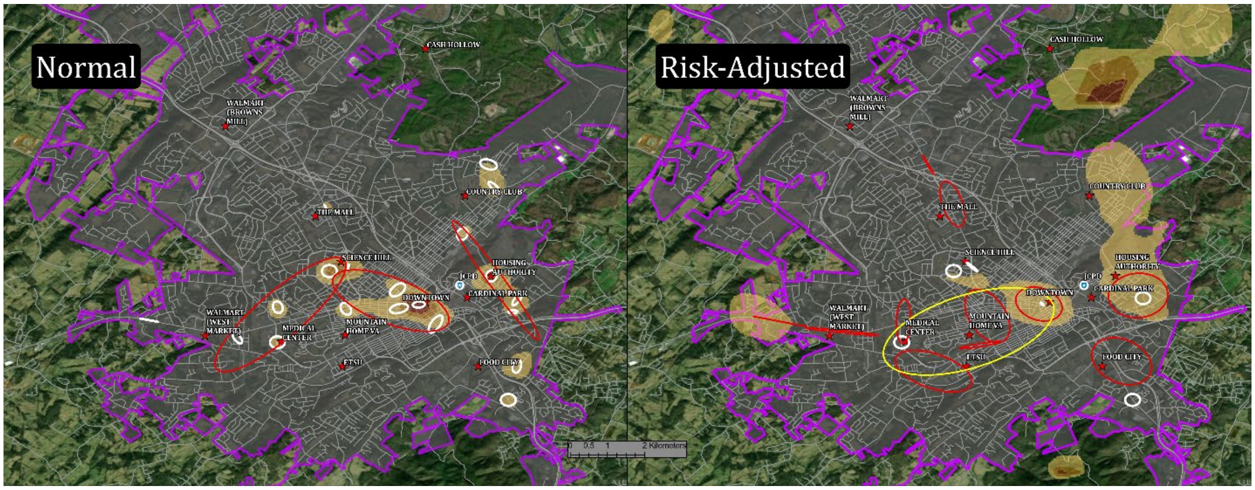

Figure 2.17. Clusters and KDE surfaces for assaults in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

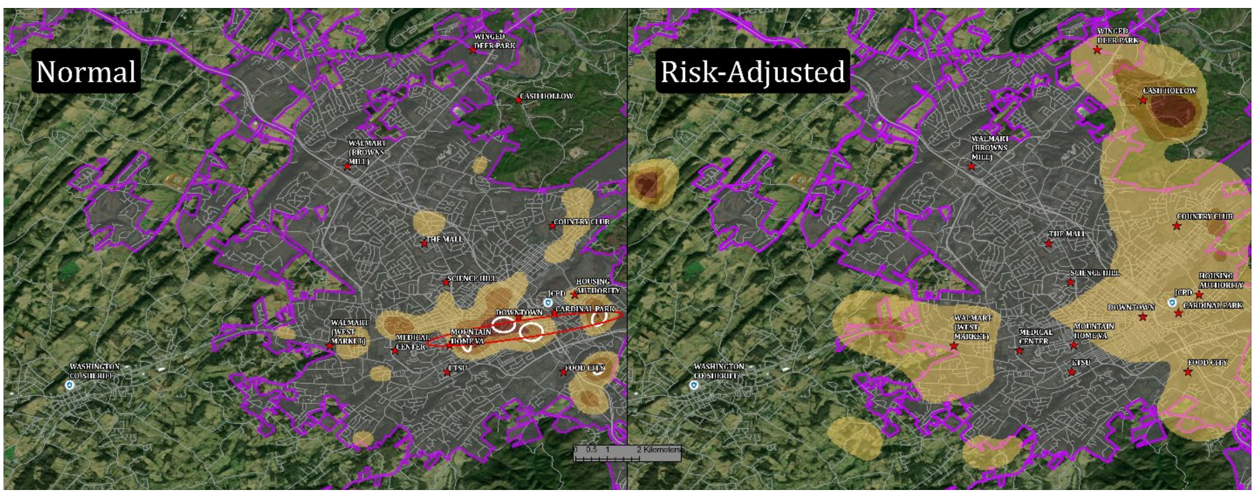

Figure 2.18. Clusters and KDE surfaces for burglaries in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

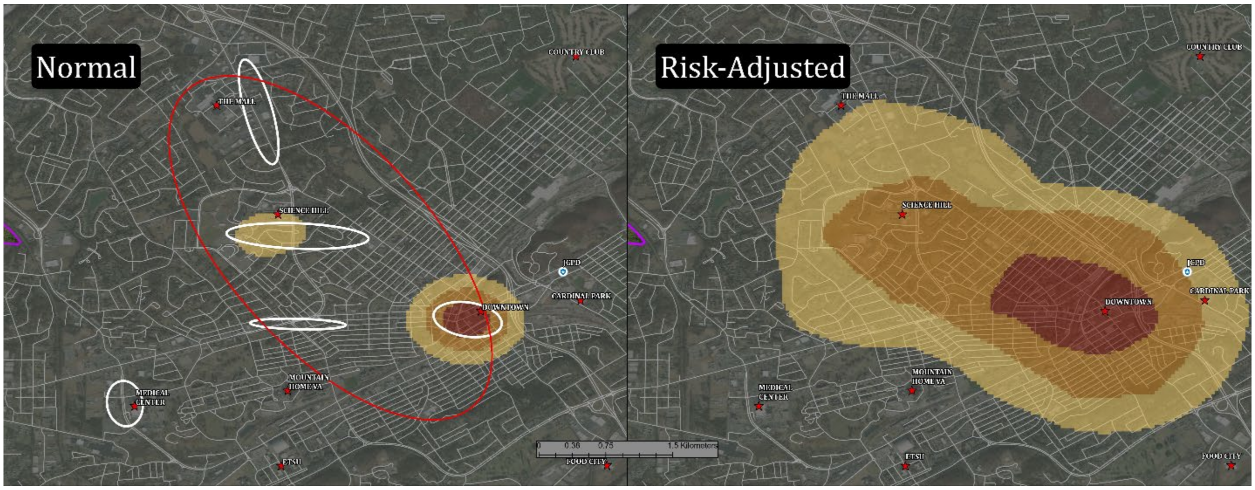

Figure 2.19. Clusters and KDE surfaces for disturbances of the peace in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

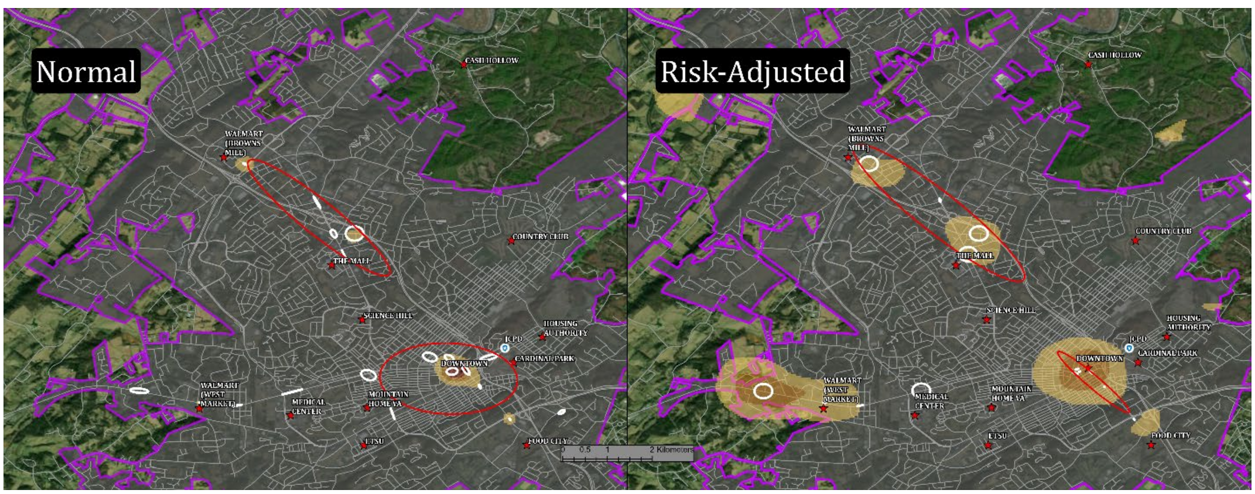

Figure 2.20. Clusters and KDE surfaces for drug and alcohol violations in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

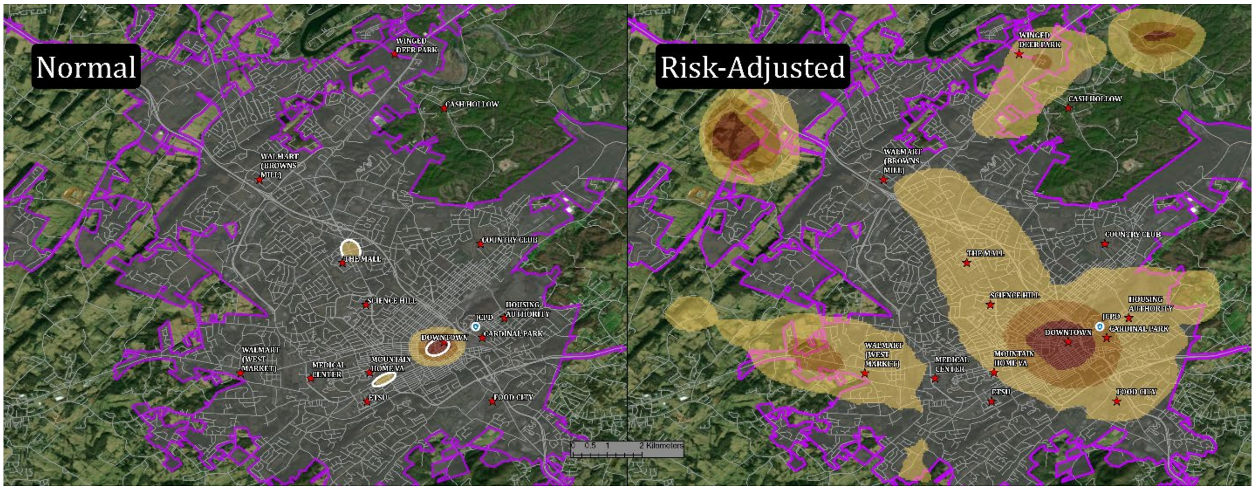

Figure 2.21. Clusters and KDE surfaces for DUIs in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

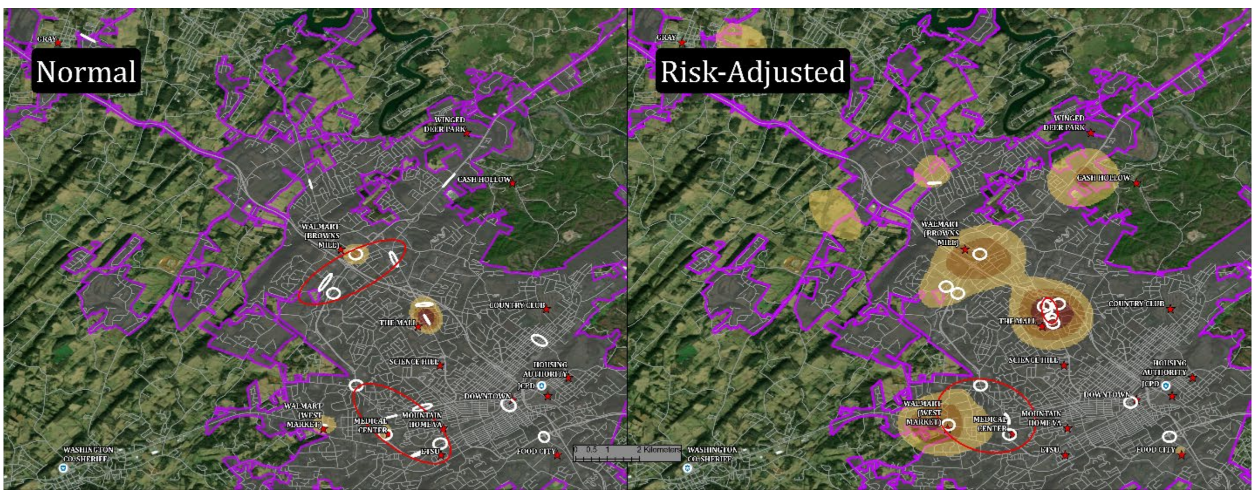

Figure 2.22. Clusters and KDE surfaces for fraud in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

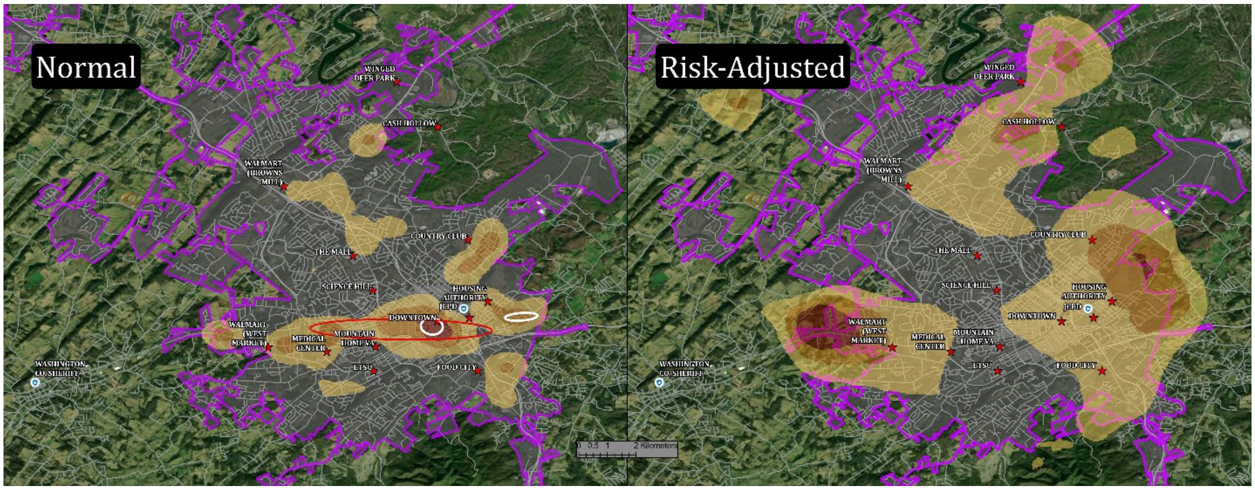

Figure 2.23. Clusters and KDE surfaces for motor vehicle thefts in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

Figure 2.24. Clusters and KDE surfaces for robberies in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

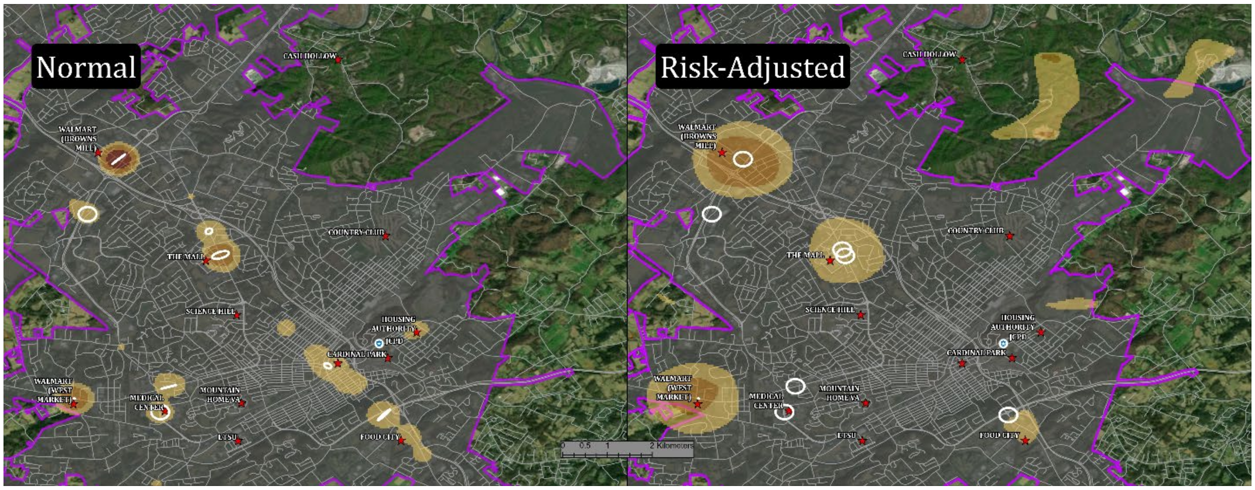

Figure 2.25. Clusters and KDE surfaces for thefts in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

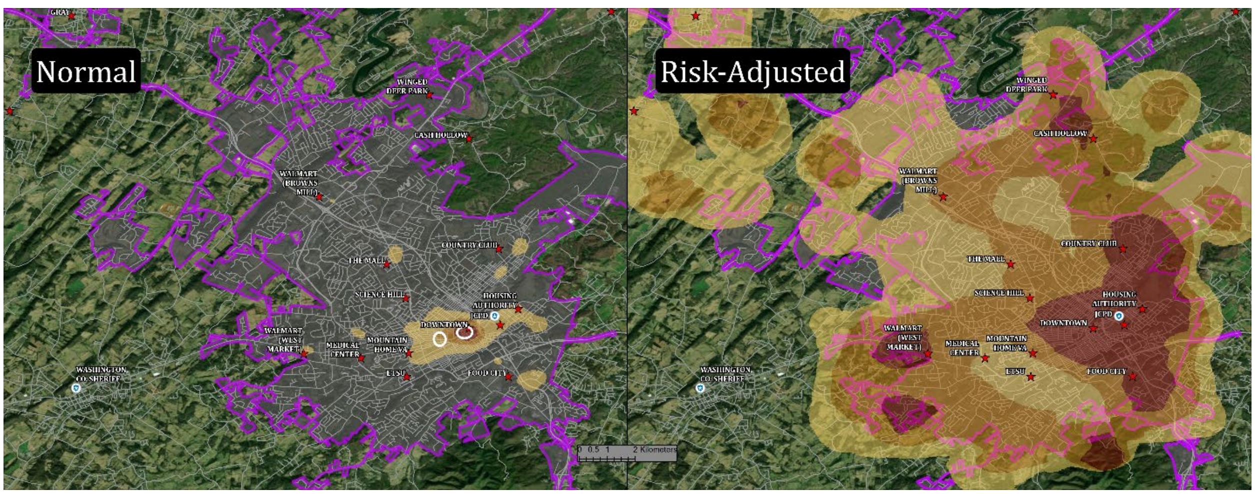

Figure 2.26. Clusters and KDE surfaces for vandalism in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

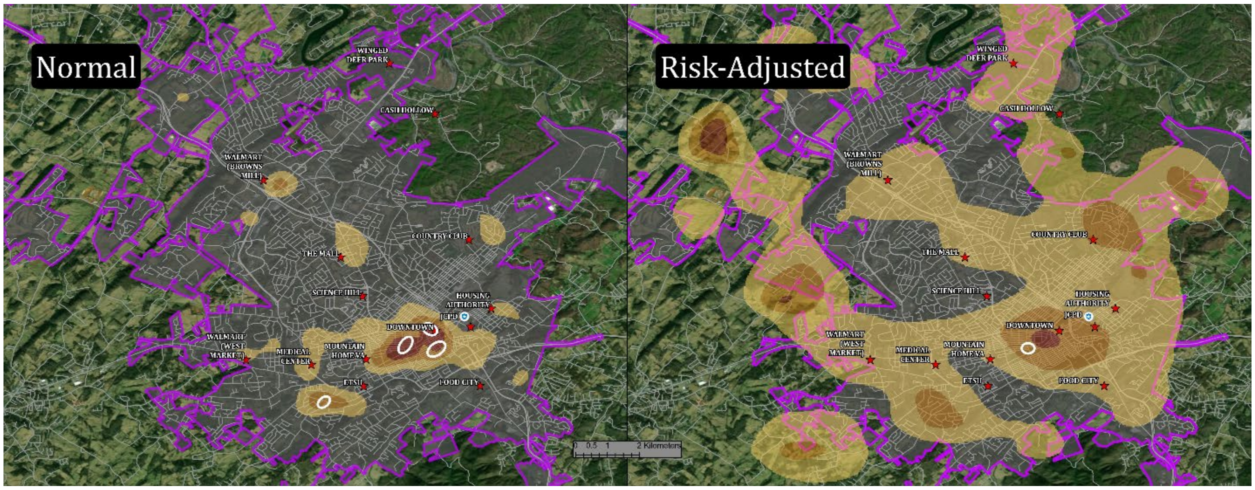

Figure 2.27. Clusters and KDE surfaces for vehicle break-ins in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

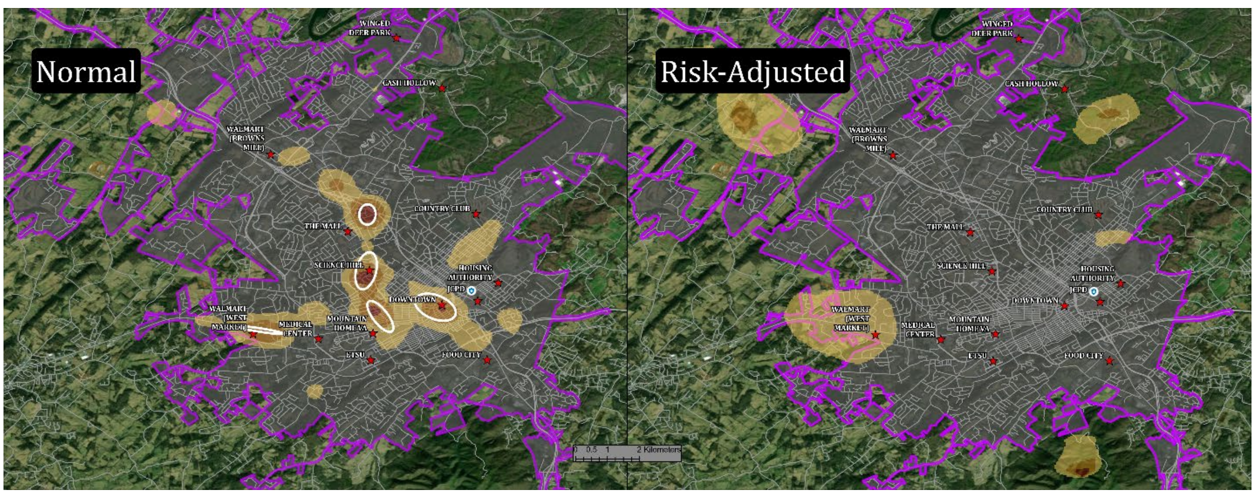

Figure 2.28. Clusters and KDE surfaces for weapon offenses in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

Clusters and hot spots for the ten most common crime categories in Johnson City result in some changes in the pattern for both NNHC and density measures, adjusted and non-adjusted compared to their respective type. Although, the problem persists with risk-adjusted methods that some categories generate no clustering or KDE calculate hot spots erroneously (Tables 2.7-2.8; Figures 2.29-2.38).

Table 2.7. Summary of areas with clustering and hot spots of crime by category.

Crime Category	Hierarchical Clustering	Kernel Density
Credit Card/ATM Fraud	Mall, Walmarts	
Drug Equipment Violation	Downtown, Mall, Walmarts	Downtown, Mall, Walmart (Browns Mill)
Drunkenness	Downtown, Tree Streets	Downtown
False Pretenses, Swindling, etc.	Downtown, Mall, Medical Center, Walmarts	Mall
Misdemeanor Narcotics	Downtown, Mall, Walmarts	
Misdemeanor Shoplifting	Food City, Mall, Walmarts, various other commercial areas.	Walmart (Browns Mill)
Misdemeanor Vandalism	Downtown, Housing Authority, some low-income residential areas	Downtown
Residential Burglary	Various residential areas both inner and outer of JC jurisdiction.	
Simple Assault	Downtown and nearby residential areas, Housing Authority and nearby residential areas, Medical Center, Science Hill	Downtown, Housing Authority, Science Hill
Theft From Building	Downtown, Mall, Medical Center	Widespread concentrations.

Table 2.8. Summary of areas with risk-adjusted clustering and hot spots of crime by category.

Crime Category	Hierarchical Clustering	Kernel Density
Credit Card/ATM Fraud	No clusters generated	Bristol Hwy, Gray, Mall, Walmarts
Drug Equipment Violation	Mall, Walmart (Browns Mill)	H-321
Drunkenness	Downtown	
False Pretenses, Swindling, etc.	Mall	Bristol Hwy, Walmarts
Misdemeanor Narcotics	Walmart (Browns Mill)	H-321, Downtown, Mall, commercial area towards Gray
Misdemeanor Shoplifting	Food City, Mall, Walmarts, various other commercial areas	Walmarts
Misdemeanor Vandalism	No clusters generated.	Downtown
Residential Burglary	No clusters generated.	H-321, residences near downtown, various low-income areas along the periphery of JC.
Simple Assault	Medical Center, Science Hill, some low-income residential areas	Cash Hollow area, Housing Authority
Theft From Building	Medical Center	No explicit concentrations.

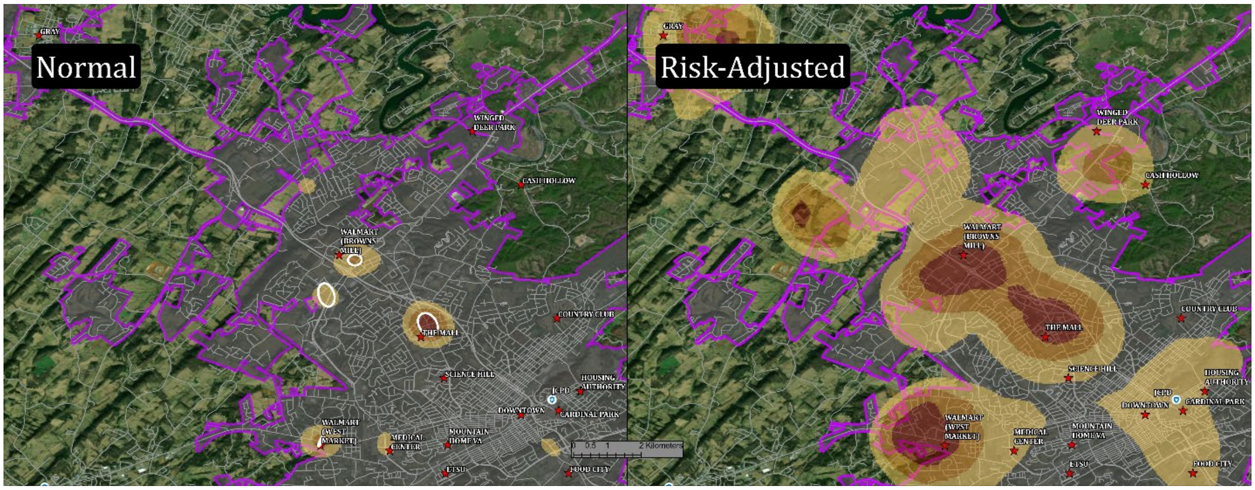

Figure 2.29. Clusters and KDE surfaces for credit card/ATM fraud in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

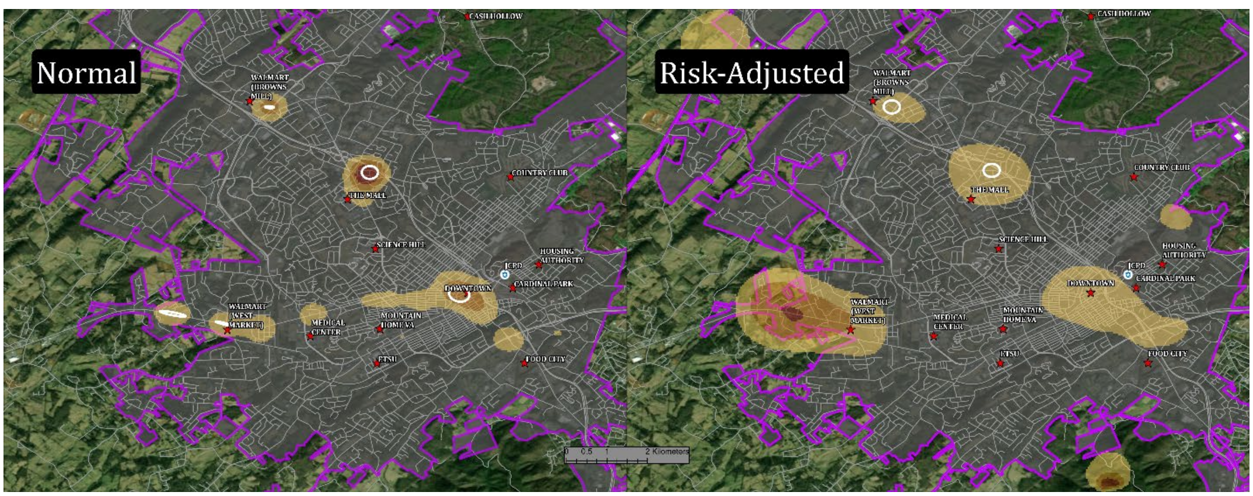

Figure 2.30. Clusters and KDE surfaces for drug equipment violations in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

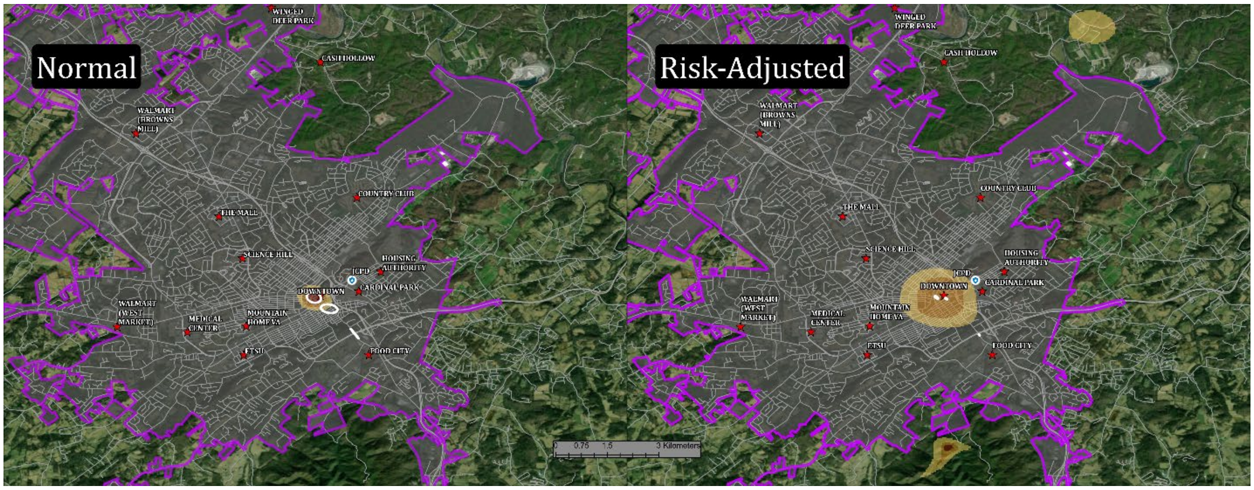

Figure 2.31. Clusters and KDE surfaces for drunkenness in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

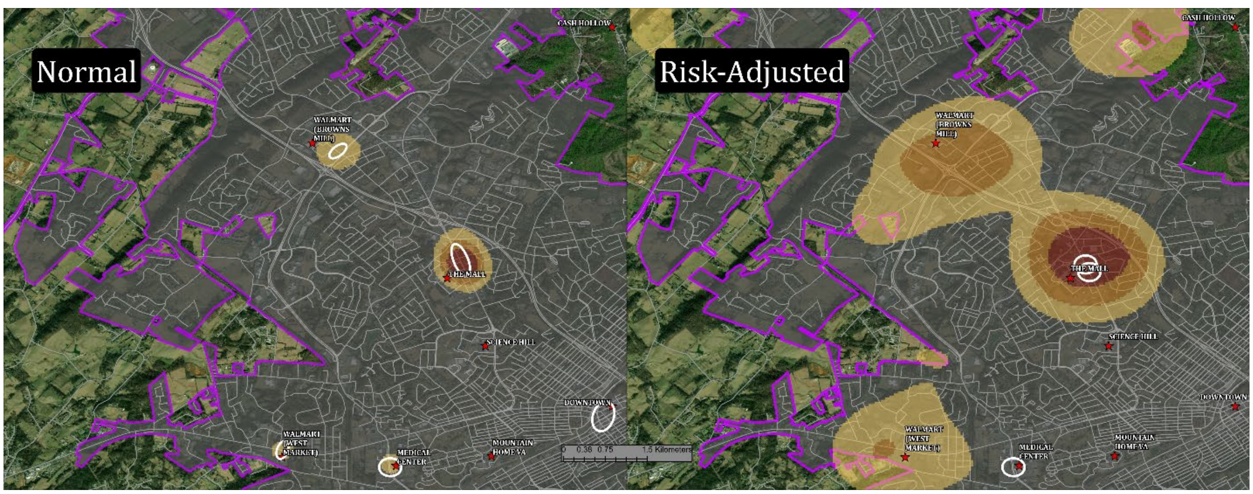

Figure 2.32. Clusters and KDE surfaces for false pretenses, swindling, etc. in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

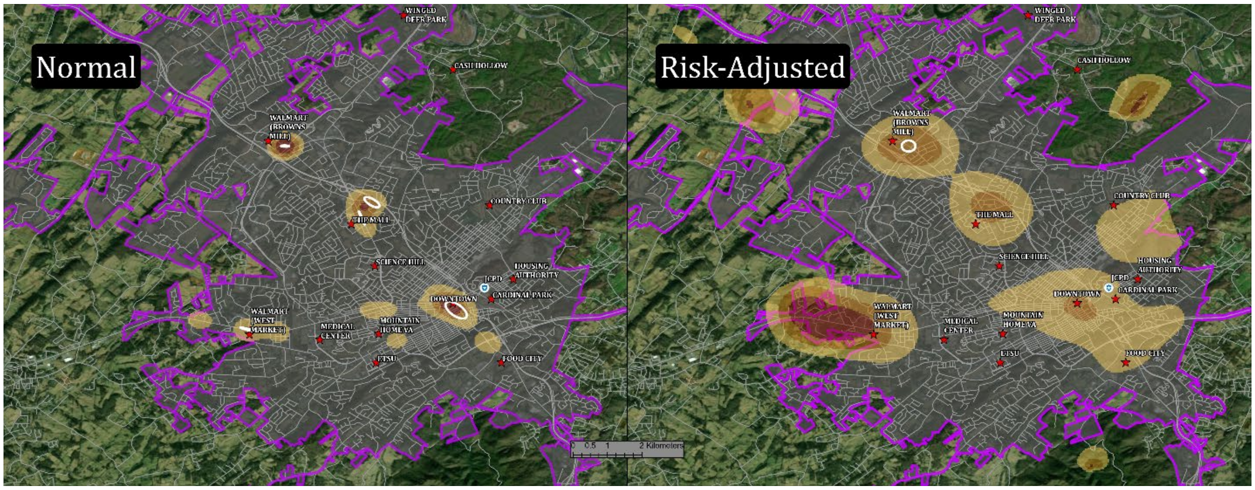

Figure 2.33. Clusters and KDE surfaces for misdemeanor narcotics in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

Figure 2.34. Clusters and KDE surfaces for misdemeanor shoplifting in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

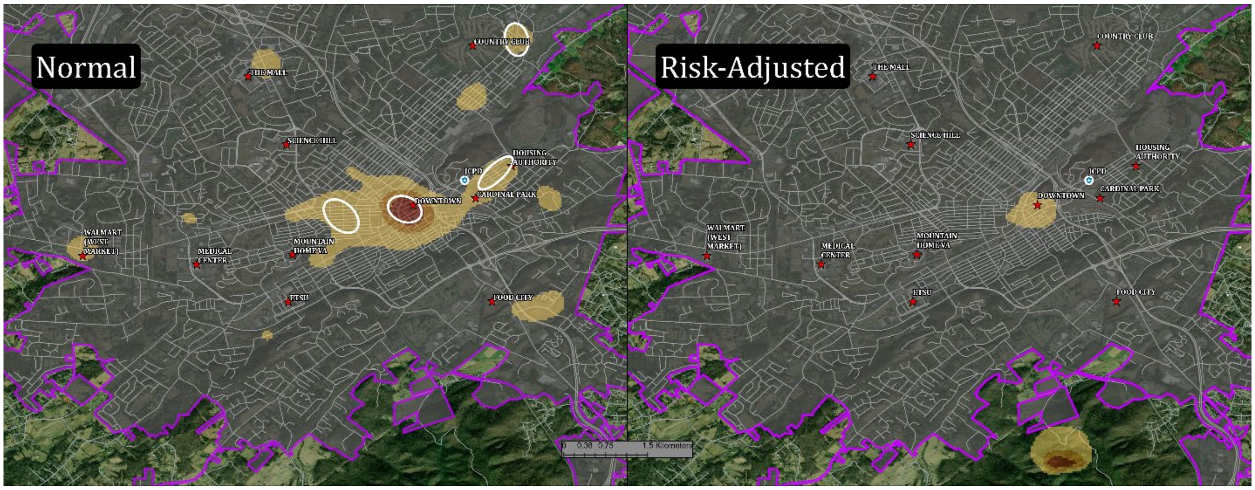

Figure 2.35. Clusters and KDE surfaces for misdemeanor vandalism in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

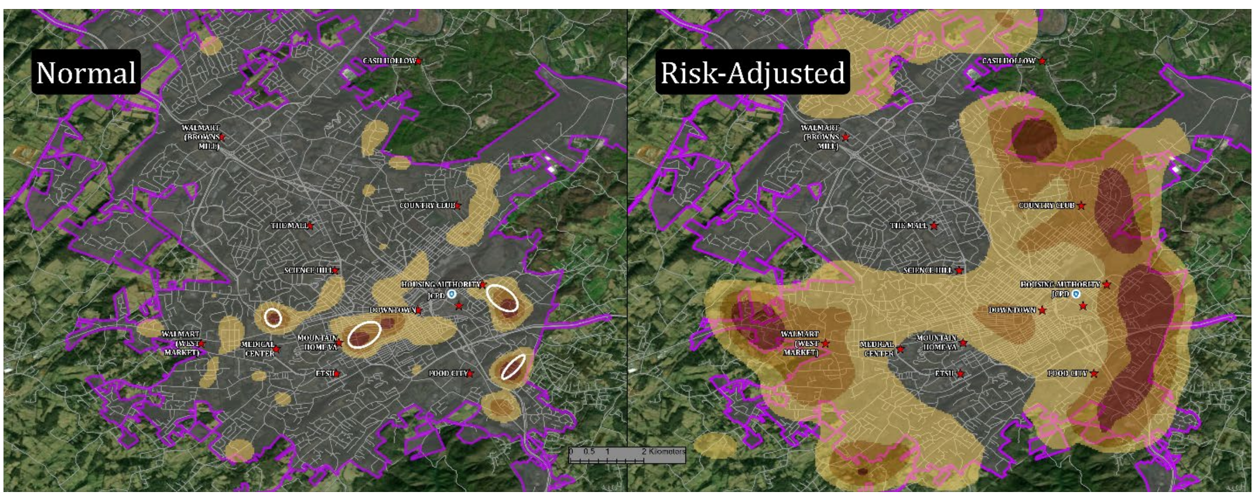

Figure 2.36. Clusters and KDE surfaces for residential burglaries in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

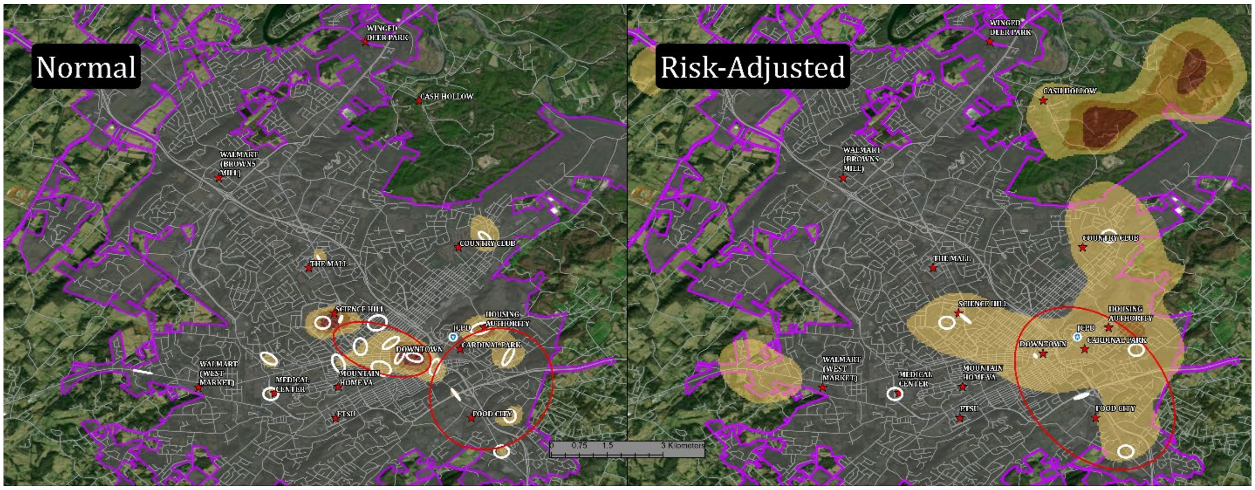

Figure 2.37. Clusters and KDE surfaces for simple assaults in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

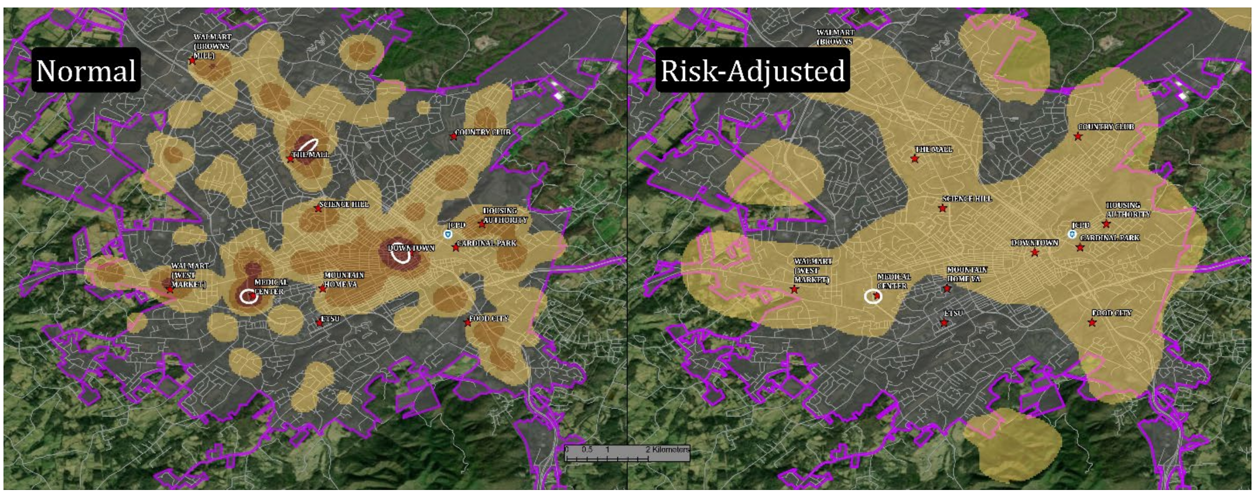

Figure 2.38. Clusters and KDE surfaces for thefts from building in Johnson City, TN (10/15/2017-06/30/2019; secondary data source: LandScan 2017™, ORNL, UT-Battelle, LLC).

Discussion

Confirming previous studies and theories areas of high daily activity, where and when people are operating within their daily routine, observe the highest concentrations of crime. Clusters and hot spots regularly occurred in areas such as downtown, places of low-income residence, areas of commerce, and along other highly trafficked roads and highways throughout town. These results appear to line up with the theory behind awareness space, that crimes occur most often around the areas offenders are most active (home, work, etc.) and the space between (Brantingham and Brantingham 1991).

Spatial analysis results became less clear when normalizing for population. While risk-adjusted results deviate, wildly in some cases, against the raw observations, it is important to consider why that may be the case. In a number of observed hot spots between multiple crime types, two main areas of interest appear where the accuracy of the calculation was frequently called into question: Buffalo Mountain to the south of the city and the residences to the northwest of the main body of the city limits. In multiple cases, hot spots calculated in these areas only included one incident (albeit in a relatively sparse area of population) or no incidents at all. CrimeStat IV documentation on dual kernel density indicates that kernels of a small bandwidth may produce surfaces where the periphery of the grid area may have overly exaggerated grid values, which can occur in the presence of an incident or even with a lack thereof (Levine 2013b). Only in a few cases did the Cash Hollow hot spots elicit a similar effect.

This calls into question the practicality of the methods employed. There is a difference between these methods regarding complexity. The only parameter that required substantial trial and error was MPPC. In comparison, KDE is much more involved with some parameters requiring a mathematical equation for various parameters, as in this case the original bandwidth calculation produced overly smoothed surfaces that were improved upon. Despite that, KDE retains popularity and a substantial body of literature that can help guide choices to make in model setup, unlike NNHC. As far as risk-adjusted methods go, there is a dearth of background literature. Adjusted kernel density generated some exaggerated hot spots, whereas NNHC sometimes did not produce any clustering. It is also noteworthy that making changes to the bandwidth on dual kernel density elicits a response much more exaggerated than a similar change on single kernel density. Potentially, introducing higher resolution population data (LandScan resolution is 0.75 km) may affect the shape of some of the odd hot spots and produce better quality risk surfaces. Further development and improvement of risk-adjusted cluster and hot spot methodologies is another area of future research.

In the context of crime, it is understandable that risk-adjusted methods garner little to no attention as law enforcement may focus on areas of high crime concentration, especially those that see frequent activity. However, there may still be insight to gain concerning neighborhoods that see more crime than could be expected given their relatively low concentration of residents. For example, many risk-adjusted hot spots appeared around the area of Cash Hollow and Cash Hollow Road, an area subject to plenty of local news articles about crimes committed there or by people from that area (Campbell 2013; Johnson City Press 2015; Thompson 2015a; Thompson 2015b; Johnson City Press 2017; Campbell 2019a; Campbell 2019b). While that and other similar areas may see regular crime, it may not get much attention from police patrols or outreach due to its relative remoteness from Johnson City.

An item to keep in mind while interpreting the results of cluster or hot spot analysis is that these, by no means, confirm that future crime will occur in those areas, only that there is a high risk for future crime to occur in those areas. However, a record of past crime may still lend insight into future crime occurrence.

Whenever performing any analysis of crime, it is also important to keep in mind that the data may not be complete; this case is no different. The data provided on CM may not be a complete record of crime reported by the JCPD, as they are the provider of the data, they may withhold data for various reasons. Further, CM discloses on their website that homicide and sex crime data are common types of crime withheld by reporting agencies. As stated before, the WCSO does include those data in their CM description, however through the JCPD data request it was discovered that they do exclude those data in addition to other criminal offenses such as embezzlement and trespassing. Excluding this, there is also the likelihood of crimes going unreported or unnoticed. This factor may have greater prevalence with certain types of crime, as the Bureau of Justice Statistics indicated that the rate of unreported victimizations differs between property and violent crimes (Langton et al. 2012).

Crimes occurring on the East Tennessee State University (ETSU) campus is another data anomaly. Despite its location in the middle of Johnson City, crimes reported to and investigated by the ETSU Department of Public Safety (DPS) do not appear on CM. An alert in November 2017 of an incident of assault with a deadly weapon occurred on campus, but no such incident exists in the data (East Tennessee State University Department of Public Safety 2017). Similarly, an incident of intimidation with threat of a firearm on the first day of classes in August 27, 2018, is not present on CM (USA Today Network Tennessee 2018). The ETSU campus represents a significant spatial void where there is a constantly high ambient population, with the thousands of resident students and commuters during the day, where crimes are known to occur but no, at least publically available, data exists for ready analysis. Public Safety produces an annual security and fire safety report, as required by law, disclosing yearly occurrence of all campus crime over the past three years. However, little to no statistical information exists in analysis of campus crime. To gain a full picture of crime within Johnson City, the dataset requires supplementation by the DPS.

It is worth repeating that addresses on CM are block-aggregated. That is, hypothetically, a crime at 305 W Walnut St would appear on CM occurring at “300 BLK W Walnut Street” in the table, preserving the privacy of all parties involved. It is not certain the extent to which this may affect the overall results, so if using CM as a decision-support tool for determining place-level remedies to crime, no small amount of caution should be exercised. It would be more appropriate to examine these results on a more general, neighborhood scale. However, police agencies can easily circumvent this issue by doing such analyses themselves using the address information police databases already contain. Conveniently, the CrimeStat software package used in these analyses, and all relevant documentation, is free for download on the National Institute of Justice (NIJ) website; although to produce maps with CrimeStat one needs to additionally install GIS software, which also has open and free options such as QGIS (if the city does not have existing GIS infrastructure).

While these types of analyses could prove to be useful support tools for local law enforcement, another application seen in other police organizations is the publishing of these data in a manner similar to CM. At the very least many police departments, using municipal GIS resources, utilize the power of ESRI’s ArcGIS Online web application development platform to create an app where recent criminal events are posted for the public to see for themselves (Halifax Regional Municipality 2019). Some try to go a step further and display results of spatial analysis, like the Brandon Police Service in Brandon, Manitoba (though as of writing, that feature appears unavailable for display) (Brandon Police Service 2019). Services such as these boost public awareness of local crime and add a layer of transparency to police activities, something over which there has been increased scrutiny (Kupferberg 2008; Jackson 2015; Sousa et al. 2018).

Conclusion

The Johnson City Police Department's current crime mitigating efforts may be bearing fruit with increases in crime reporting. Investigation into potential problem areas of Johnson City may give additional insight into neighborhoods that the police may provide further investment of time and resources to alleviate crime through patrols or a tailored, more community-oriented approach. Normal cluster and hot spot analysis can confirm whether areas of constant, significant, daily activity (e.g., downtown) contain concentrated criminal activities and bring attention to other areas of unusually high activity. Risk-adjusted methods, if carefully used by an analyst knowledgeable of the data who can identify and ameliorate erroneous results, can identify additional areas that, while not particularly abundant in criminal activity, appear to elicit more crime than a neighborhood of its size would normally have in relation to the rest of the region. Data anomalies can be smoothed out with additional data sources and access to accurate address information, both of which local law enforcement can leverage alongside free software to have more freedom with their data, and without subscribing to a data storage service. This could ultimately culminate in a department's own custom web-based application, developed as a tool for police strategy and community awareness.

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CHAPTER 3

GEO APPS AND DASHBOARDS: CONTEMPORARY TECHNOLOGIES FOR DATA DISSEMINATION AND CONSUMPTION

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Abstract

Advancements in geospatial technology and the Internet of Things brings the ability to create and share map-based products on a large scale. Esri and other organizations are beginning to provide resources and services to groups such as law enforcement agencies, among others, to enhance their capabilities. Operations Dashboard, a report-style web application, is one tool in the toolbox for the analyst. With little to no coding needed and easy-to-customize map-based widgets, analysts of all levels of expertise can make graphics-based applications for decision-makers and various other audiences. In this case, dashboards present an opportunity to glance at crime trends in space, place, and time; maps and charts give an idea of areas and times of potential high criminal activity for police officers. If this application is publicized, citizens and neighborhood watch groups who are concerned about crime in their community and city can also utilize its analytics. This not only makes the dashboard a useful tool for quick at-a-glance analysis in crime mitigation, but also provides an interface between local law enforcement and the citizenry.

Keywords: Geo Apps, Operations Dashboard, crime mapping, open data, web GIS

Introduction

Working as a data scientist in the field of geographic information systems (GIS) and remote sensing in contemporary times is exciting with ongoing advancements in the Internet of Things (IoT). This interconnectivity of technological networks, its rapid advancements, and its accessibility and availability to a wide range of users, brings new opportunities to interact with that technology (Joyner & Mollenkopf, 2018). At the forefront of this innovation, over the last few decades, web GIS saw increased adoption and use by businesses, government agencies, and other entities. The wide reach of the Internet, ease of use and maintenance, and diversity of applications provides an ideal channel through which data can be disseminated throughout an organization, group, or even to the public (Fu, 2015).

The Environmental Systems Research Institute (also known as Esri), one of the most influential businesses in geospatial data science, championed the advancement of GIS into the IoT. ArcGIS Viewer for Flex was one of Esri's first forays into web mapping, an application for developers and non-developers alike with a customizable graphically driven interface. Getting the most out of Flex requires extensive widget programming and API (application programming interface) support (Esri 2014). More recently, Esri brought renewed vigor to ArcGIS Online (AGOL), with greater capabilities and new utility beyond basic map viewing with limited functionality. Now with AGOL, investigators can upload, analyze, and share data, collaborate on projects, and leverage their creations to create impactful tools (Esri).

Esri provides multiple platforms on AGOL to create data-driven web products. Dashboard type applications, such as Operations Dashboard for ArcGIS, provide simple report-like interfaces, driven by widgets, which include maps, charts, filters, etc., for at-a-glance decision-making. Operations Dashboard provides a simple-to-use engine to develop a dashboard application without requiring any programming expertise (Esri; Pelletier). This accessibility lends to its popularity as a platform for sharing data and generating statistics. Public safety is an industry seeing increased implementation of web applications for such purposes. Researchers and law enforcement agencies on all levels of governance over the last few years have taken advantage of Operations Dashboard's capabilities as a data visualization tool (City of Brasilia Brazil; Jumonville 2018; Douglas County Sheriff's Office 2018; Ogden 2018; The Vancouver Police Department 2018; Beck 2019; Brandon Police Service 2019).

While Esri dominates the web-mapping arena, they are far from the only company providing web mapping services. Websites such as TriTech's CrimeMapping (CM) and LexisNexis's Community Crime Map (CCM), formerly known as RAIDS Online, allow subscribing law enforcement agencies to curate criminal occurrence data in their jurisdiction for users to view with some charts and other graphical analytics (TriTech Software Systems 2016; LexisNexis 2019). Among their analytics, CCM provides a unique visualization of temporal hot spots per day of the week by hour (LexisNexis 2019). Services like these benefit police in municipalities lacking GIS infrastructure, but largely do not provide anything special for those that employ a GIS analyst.

Methods

For this application, the Operations Dashboard platform serves to display information on the distribution of crime within the city of Johnson City (JC), Tennessee in time and space. To create an equal emphasis between these aspects of the data, a combination of cartographic techniques and charts will be used to display aspatial trends. The main objective is to create an application that displays the data in a manner that makes it accessible for the widest range of people, both civilian and police, as possible.

Outside of increasing awareness for the public and supplying local police with an on-the-spot decision-making tool, this application serves an additional, pragmatic purpose. Currently, the Johnson City Police Department (JCPD) subscribes to the CrimeMapping (CM) web mapping service. This service holds up to 180 days of crime data volunteered by subscribed agencies, updated daily. These data are separated into crime types based on how these crimes are described (e.g., shoplifting is arranged into the "theft/larceny" type). Since law agencies completely volunteer this information, they have the prerogative to keep small, relatively nonconsequential, offenses from cluttering the map or to withhold very severe or sensitive offenses from public display (CM disclaims that many agencies do not volunteer homicide and sex crime data). A new web application for the JCPD that fulfills the same tasks as CM plus any additional items of interest to the department could provide a useful alternative for the department since Johnson City has existing municipal GIS infrastructure. CrimeMapping does not advertise any subscription cost for their service, so the amount of money the department would save by switching is unknown.

Case Study – Philadelphia Demonstration App

The development team of Operations Dashboard for ArcGIS demonstrated the ability of Operations Dashboard as a tool for at-a-glance decision making by creating a dashboard using open data from the Philadelphia Police Department (PPD). Upon opening the dashboard, users are presented with a map, front and center, of all Part I crimes (arson, aggravated assault, burglary, larceny, motor vehicle theft, murder, rape, robbery) over the past 28 days sized by the time elapsed since (last hour, last 24 hours, and older). In the same panel, below the map, are several serial (or bar) charts displaying total amount of crime per crime type separated by city police division (which represents the geographic split between police districts (e.g., North West Police Division or NWPD) (Operations Dashboard Team (Esri) 2017).

In addition to the map and charts, users may move between three other tabs in the center panel for additional data. The "time periods" tab displays a pie, serial, and line chart, each displaying temporal trends in the full 28-day period by time of day, day of the week, and hour of the day, respectively (Operations Dashboard Team (Esri) 2017). There is a purpose to using both a pie and line chart to display these kinds of data. The pie chart shows the relation of crime over a specific "block" of the day, showing when a majority of crimes occur over the day. The line chart shows the progress and regression of crime through the natural course of the day. Next, the "Last Days Comparison" tab compares crime in the last 14 days to the same 14 days from the last year, showing a percent increase or decrease, and does the same for the last 15-28 days. Lastly, the "Property and Violent Comparison" tab does the same as the previous tab but with Property and Violent crimes over the past 28 days (Operations Dashboard Team (Esri) 2017).

On the right-hand panel is a live crime feed complete with a numerical indicator and list of all crime in the period, with associated date and time of incidence and block-aggregated address. Users are able to filter the data down to a 7-day, 3-day, 24-hour, or the last hour interval instead of the default 28 days. Should the user wish to further explore the data in other ways, filters are present on the left-hand panel for filtering by police division or district, crime type, day of the week, and/or time of day (Operations Dashboard Team (Esri) 2017).

This Philadelphia app is thoroughly resplendent with data with a multitude of filters to customize the data display that could allow users to observe crime over a relatively macro spatiotemporal scale, or extremely specific micro-scale such as burglaries occurring mid-day on Saturdays within the NWPD. While a large police department in one of the United States' most populous cities no doubt could find all of this information useful, such a comprehensive undertaking in managing all of these data may not be so paramount for the management of police resources in a smaller community like Johnson City. Moreover, when developing an application with the intent of being useful for both the police and public, displaying all data could potentially feel overwhelming to an individual inexperienced in data consumption. A balance must be struck, displaying sufficient data in both a functional yet approachable manner.

Case Study – Halifax (Nova Scotia) App

Another unofficial Operations Dashboard exists for the display of crime in the Halifax Regional Municipality (HRM) in Nova Scotia, Canada (Figure 3.1). Similarly, the Halifax Regional Police (HRP) hosts this information, which consists of certain types of crime within a seven-day period. Unlike Philadelphia, which displays all Part I index crimes, the HRP dataset only contains assault, breaking and entering, robberies, thefts from vehicle, and thefts of vehicle. The map takes up the majority of space on the app, displaying the incidents throughout the region. To the left of the map are an indicator of the crime on display and a stack of graphs, one bar and one pie, of crime separated by type. On the top right corner of the dashboard is a dropdown filter for isolating crimes based on their type (Ogden 2018).

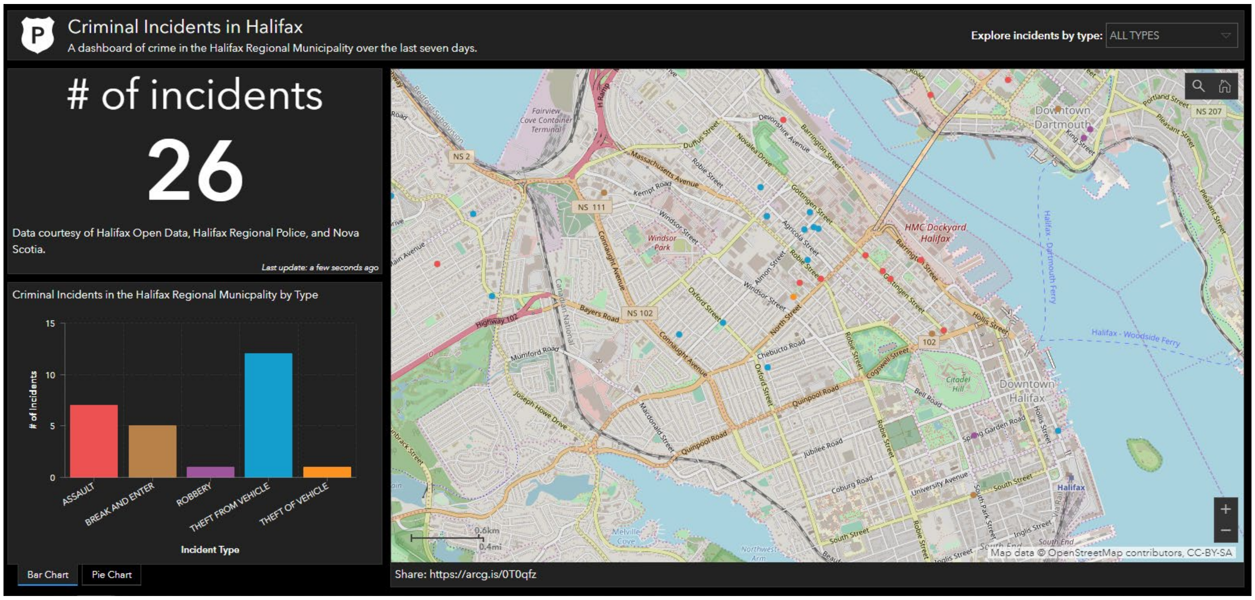

Figure 3.1. Screen capture of the Halifax criminal incidence dashboard.

The Halifax app is not as data-rich as Philadelphia's but it makes up for that in its approachability to a public inexperienced in data consumption. For the Johnson City app, something between those two applications may work best.

Johnson City Crime Operation Dashboard

Using the two previously discussed applications as a guide, an online operations dashboard application is designed for the intention of use by both the police and public to observe crime trends. The only requirements to view the dashboard will be an internet connection, web browser, and of course a link to navigate to the application (Figure 3.2).

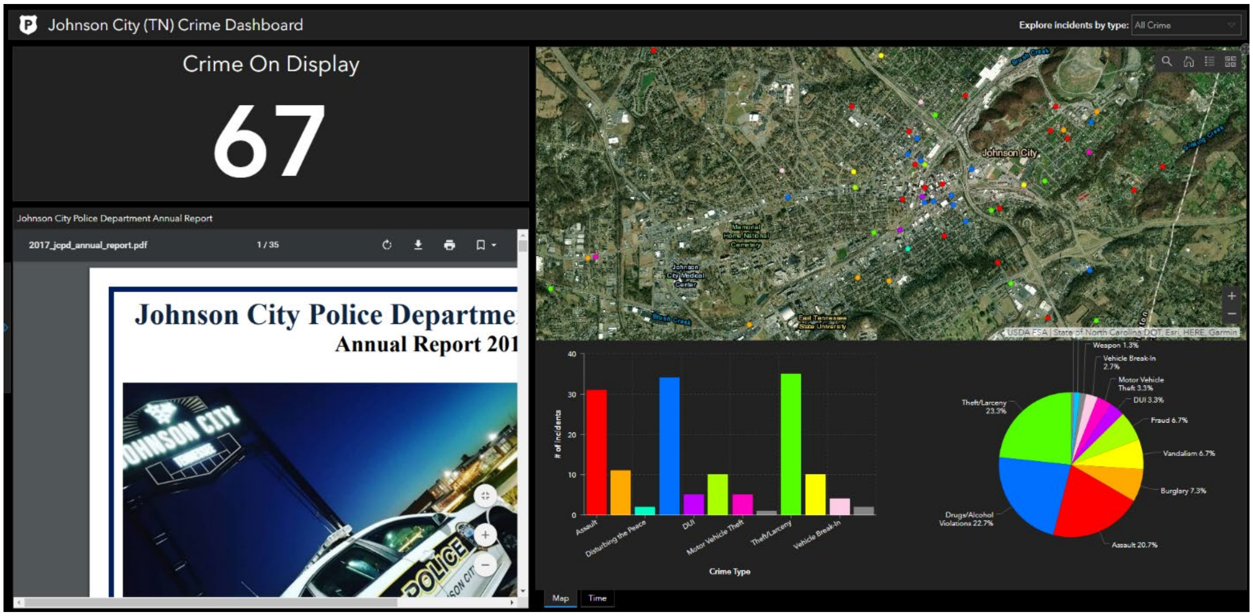

Figure 3.2. Screen capture of dashboard interface upon initial application load from a viewer's perspective.

The principal component of the dashboard on which all other components are built around is the web map containing criminal incident data. In lacking live or regularly updating data for demonstration of this application, currently the dashboard uses an upload of some placeholder crime data for Johnson City from 10/14/2017 – 06/29/2019, symbolized by crime type. When the application launches, so that a veritable swarm of incident points does not overwhelm the user, a filter tones down the dataset so only incidents between the last seven days of the available data will appear. Users may extend or shrink the time interval beyond the default. Crime type is an additional filter applicable to the data via a dropdown menu in the top right corner of the dashboard. Each filter affects the data displayed on the map and the various widgets, allowing for a wide range of customization options with the data.

A search bar allows the search of a specific address, whether it be an actual incident location or a user's residence or business to check for nearby incidents. Appended to the map, charts compare crime types between each other and crime overall.

A second "Time" tab on the main panel displays the map data in a temporal context. On top is a line chart displaying crimes throughout a 24-hour period, beneath which two bar charts lie. To the left is a serial chart of crimes split between days of the week, where "1" represents Sunday and so forth. To the right, similarly, is a month of the year chart, where "1" represents January (Figure 3.3).

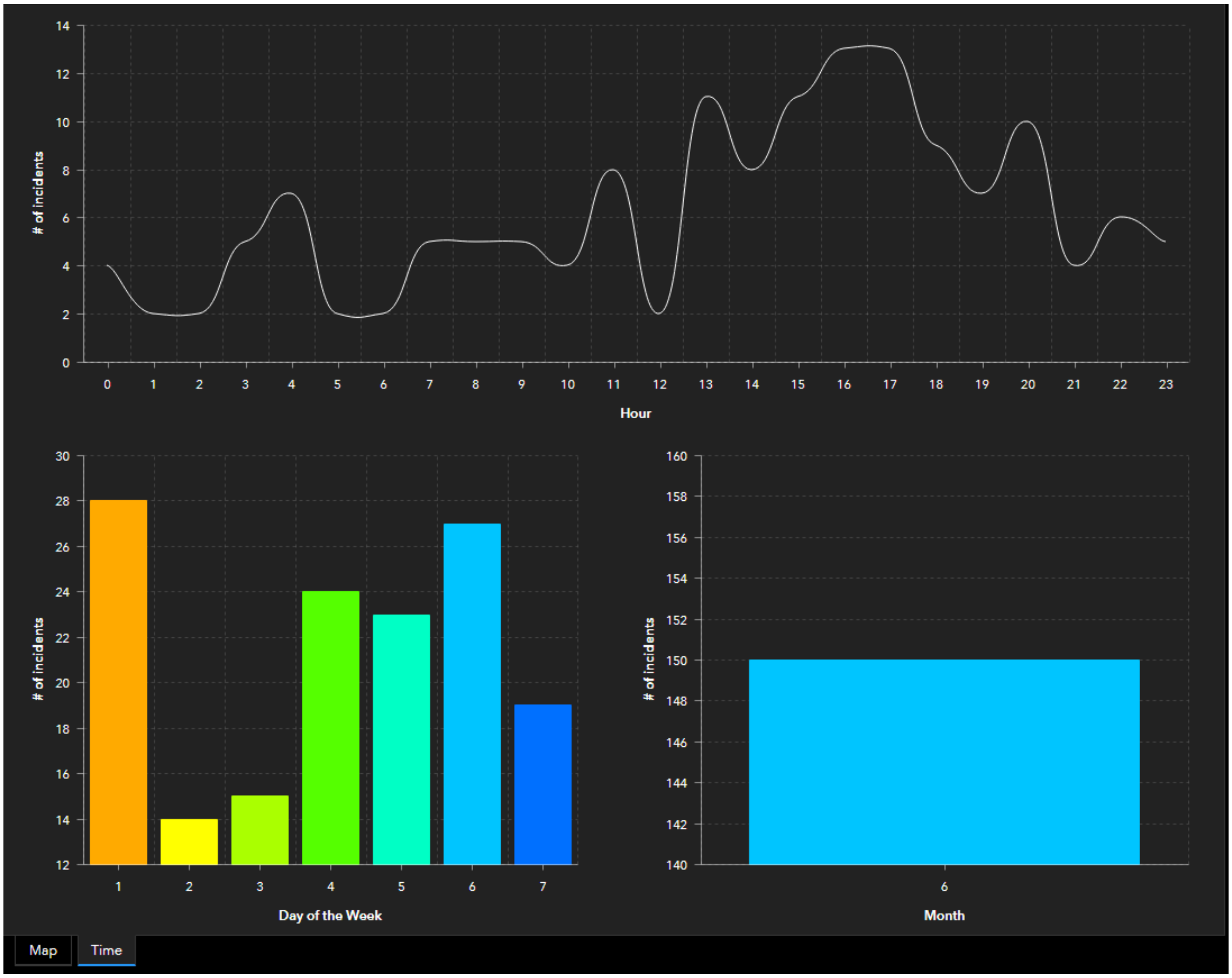

Figure 3.3. Time tab of dashboard main panel (data displayed from June 23-29, 2019).

To lend additional context to the dashboard, the most recent (2017) annual crime report by the JCPD is embedded to the side allowing users to peruse through its entirety or download a copy onto their computer. The report sits under a simple indicator of all crime on the map display, changing with filter usage and change in map extent.

Hovering over a panel (annual report, indicator, and map/time) reveals a button on the top right corner of that panel allowing the viewer to enlarge that panel to cover the whole window. Use of this feature may only be particularly beneficial with respect to reading the JCPD annual report without relying on the use of multiple scrollbars.

Discussion

The Johnson City crime application displays the capabilities of Operations Dashboard as a data visualization and analytics tool. Operations Dashboard produces applications with the potential to assist decision-makers in allocating resources and manpower; implementations of which police entities are increasingly taking notice and advantage (Jumonville 2018; Beck 2019). With persistent advancement in web GIS and IoT, the power of geospatial data cannot be understated. With increasingly smart and community-driven police forces, along with the barriers to entry in GIS falling, emerging tools will increase their capabilities to mitigate criminal behavior.

The introduction of this application grants users a means to observe local crime trends in the short and long term in both a spatial and temporal context. For civilians, this application lends itself as a tool for boosting awareness of local crime. The application is also an instrument providing results at a glance for decision-makers to allocate resources to mitigate the social issues and issues of perceived opportunity in the neighborhoods of high criminal activity.

Crime dashboards and similar applications may additionally serve as an interface between law enforcement and local citizenry. The JC crime dashboard adds a new avenue for citizen involvement in crime reduction in collaboration with the JCPD, in addition to current and proposed programs (e.g. neighborhood watches and associations). These kinds of community interaction and initiatives provide a focus for police agencies alternative to some of the more aggressive enforcement procedures criticized by the public. While web applications and maps cannot replace direct interaction with actual sworn police, they are nonetheless a potential mechanism to inform and drive interest to local crime phenomena.

Additional features were considered for the app but were ultimately not implemented due to data constraints and limitations of the program. One function, of which the JCPD expressed interest, is an alert system for residents when a burglary occurs within their neighborhood. CrimeMapping, the subscription service the JCPD currently use for mapping crime, allows users to sign up to receive an email alert when a crime occurs within a distance from their residence. This centers around the theory of repeat (or near repeat) victimization where a criminal who successfully burglars a house then recommits that offense shortly after the previous incident (Kleemans 2001; Townsley et al. 2003; Bernasco 2008). The JCPD also expressed interest in a feature similar to one present in the Philadelphia dashboard, a group of charts and indicators for comparing the last seven days in crime to those same days last year to see the difference in crime. Future updates on the app, or work on a new app, or updates to the Operations Dashboard development platform could see these desired features implemented.

Conclusion

The Johnson City Crime Dashboard (accessible at https://arcg.is/10zPWq) provides a simple, yet functional, window through which users with any level of experience can view trends of local crime in the short or long term.

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CHAPTER 4

SUMMARY OF FINDINGS & FUTURE RESEARCH

Summary of Findings

Geospatial techniques such as cluster and hot spot analyses continue to be tried-and-true methods to analyze spatial trends in crime. Clusters and hot spots grant insight into neighborhoods of high crime density, identifying areas of high risk. Temporal analyses looking at daily, monthly, and hourly crime trends supplement the spatial data to form a more complete look at crime. The results of these analyses can inform decision-makers in law enforcement agencies with improved resource management. Publicizing these kinds of data for public consumption may also prove beneficial, as there are many benefits in public participation in crime-mitigating efforts. In this case, a web application showing the distribution of crimes in a city can boost the public's awareness of local crime occurrence, showing what types of crime are prevalent, and adding a measure of transparency to police activity.

Future Research

Several restrictions, such as data availability and address aggregation, limited the ability to engage in certain types of analyses. Future endeavors in crime research in Johnson City can take advantage of new or historic data to develop results that examine and interpret local crime trends. Some ideas where prospective research can go include:

- Place-level analysis using non-generalized location information.
- Reanalysis using crime categories not included in CrimeMapping or in this analysis.
- The short-term and long-term effects of downtown revitalization on crime.
- Crime trends related to holidays and holiday seasons.

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APPENDIX

Data Sources

Crime occurrences / Primary Data

- CrimeMapping
    - Johnson City Police Department
    - Washington County Sherriff's Office

Crime occurrences (aspatial)

- Johnson City Police Department

Secondary Data

- LandScan 2017™, ORNL, UT-Battelle, LLC

Reference Data

- Cities - National Transportation Atlas Database via the Homeland Infrastructure Foundation-Level Data
- State boundaries – U.S. Census Bureau TIGER/Line
- Local Law Enforcement Locations – Homeland Infrastructure Foundation-Level Data
- Roads – City of Johnson City
- Land Use – City of Johnson City
- City Limits – City of Johnson City

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