A GEOSTATISTICAL ANALYSIS OF CRIME IN SEATTLE CONSIDERING INFRASTRUCTURE AND DATA-MINED COLOCATION

by

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DEDICATION

This thesis is dedicated to my loving parents Jacqueline and Gerald Delts, my sister Inga, nephew Alex and my missing rib. (Domus nostra pugna conficitur)

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LIST OF ABBREVIATIONS

Research Question ....RQ
Research Question 1 ....RQ1
Research Question 2 ....RQ2
Pattern Analysis .... PA
Squared .... SQ

ABSTRACT

A GEOSTATISTICAL ANALYSIS OF CRIME IN SEATTLE CONSIDERING INFRASTRUCTURE AND DATA-MINED COLOCATION

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One of the most persistent problems in our society is criminal behavior. Crime persists regardless of perceived punishment and the increased focus of law enforcement.

Objective: This thesis examines the hypotheses that specific infrastructure types can have impacts on crime densities in Seattle, Washington, and examines crime type occurrence by census blocks to observe if predictive crime pattern identification is possible.

Method: The hypothesis for the significance of infrastructure on crime density is assessed by the distance-based application of the T-test for significance. The predictive crime pattern analysis hypothesis is evaluated with data mining using the Apriori algorithm to develop association rules that are predictive based on existing crime in the census blocks.

Results: Both hypotheses demonstrated varying amounts of success, indicating that infrastructure does have a significant effect on crime density and that predictive data mining algorithms can create crime association rules.

Conclusion: The results suggest that specific types of infrastructure do have a direct relationship with crime density in the immediate surroundings and Bus Stops, Religious Centers demonstrate higher significant effects than others when paired with specific types of crime. The pattern analysis results demonstrated that crime association rules are possible and can be used to predict crimes occurrences based on the type of crimes are reported in the surrounding area.

1. **INTRODUCTION**

As the world's technology advances and societies move towards a more progressive self-aware state, there are few persistent problems that affect every society throughout the world, regardless of location, ethnic background or economic standing. One of these persistent problems is criminal activities. These activities are a constant threat to every single person living in an organized society throughout the world. With the world's numerous advances in technology, criminals have found many ways to adapt and survive in the modern world.

Traditional researchers have always attributed crime prevalence to a lack of education, a reduction in law enforcement and lower employment (Hope, 1995). To reduce this persistent threat, the world has increased its overall police presence. Increased law enforcement has helped; however, it does not provide a complete solution. Instead, its effect is more of a mitigation strategy or an after-action approach, rather than a preventive measure. The goal going forward should not be action after a crime has been committed, but understanding and eliminating crime as a persistent problem. A combination of geospatial statistical science and spatial data mining can advance the goal of crime elimination.

Over the last few years, geospatial data has experienced a significant increase in its availability through its publication on the World Wide Web, and this increase has benefited the field of geospatial analytics by demonstrating its ability to assist in solving non-spatial problems (Usman, 2015). This increase in geospatial data availability has become a driving factor in a new age of geospatial analytics. Geospatial analytics are not just defining the effects of crime; they assess root causes and provide potential theories on sources (Chamikara, 2014). The application of geospatial analytics to non-spatial problems is not a new field of science. Geospatial analytics has demonstrated its ability to solve problems; a historical example of this can be traced back to1854 when Dr. John Snow used geospatial analytics in studying the cholera outbreak, to determine its root cause (McLeod, 2000). In the past, spatial analytics in conjunction with crime frequency data could generate heat maps determining areas of high criminal activity (Hua and Brown, 2003). The value to the analytical community was limited to the fact that certain areas have substantially more documented criminal activity, which then gave rise to targeted policing. When analyzed in tandem with the spatial environment data researchers focused on the environmental factors that coincided with an increased probability of crime with few concentrating on factors that could reduce the probability of crime (Hua and Brown, 2003). Geospatial statistics studies tried to establish a linkage between alcohol availability and criminal behavior using the clustering and colocation methods to support the theory that criminal behavior tends to co-locate in areas with alcohol availability (Roncek and Bel, 1991, Ratcliffe, 2012). Alcohol may be a factor in the decision-making process; however, its impact on criminal activity is negligible because crime can occur while perpetrators are not under the influence of alcohol. Additionally, this kind of geospatial statistic does little to provide insight into the source of criminal behavior.

1.1 Problem Statements

There is no doubt that alcohol and economic conditions have an impact on the amount of criminal behavior present in an urban environment. The current scholarly understanding is that neighborhoods with high crime rates are associated with higher levels of economic disadvantage, larger proportions of young people, and greater residential instability (Wang, et al., 2019). Various researchers over the last decade such as Roncek, Bell, and Ratcliffe and even more current studies by Wang, Lee, and Williams have observation and documentation of these environmental behavior patterns (Roncek and Bel, 1991, Ratcliffe, 2012, Wang, et al., 2019). However, when analyzing an environment from a geospatial perspective other institutions besides liquor procurement define communities' composition. The acknowledgment of this fact indicates there are potentially other factors that could be providing significant influences on criminal behavior. Understanding infrastructure effects presents the possibility that the spatial location of other facilities does have an undocumented impact on criminal behavior in the same way alcohol procurement effects violent crime in the area. (Ratcliffe, 2012)

Studies have suggested that land use does play a larger role in criminal behavior in a community. (Brandon, et al., 2018). Proposed effects go so far as to theorizing that certain land use features are exerting a pervasive influence on crime. (Kubrin, et al., 2011) This study examines the relationship between criminal behavior and community infrastructure to determine if certain characteristics of infrastructure exhibit any significance on criminal behavior in their immediate surroundings and if spatial crime patterns can generate persistent association rules.

1.2 Hypothesis

After reviewing the studies of Ratcliffe and Roncek there is the potential for a counter-theory that challenges their assumptions about crime colocation. The purpose of this study is to test the assertion that crime colocation is the byproduct of poor community development and that certain features in a community can affect crime density, while investigating the idea of data mined crime patterns can be an alternative to predictive heat maps. This study will also attempt to validate the argument that crime density reduction is possible through the colocation of certain aspects of our society. This study is going to use community infrastructures like schools, parks, religious institutions, bus stops, and emergency stations as centroids to explore crime density in the immediate surroundings. This will be tested through a combination of spatial data mining and geospatial statistics when applied will provide a representation of how significant infrastructure facilities are in comparison against criminal behavior. Another insight this research will provide is the potential to develop predictive patterns of criminal activity not based on hotspot analysis, but on criminal behavior patterns in the census blocks. This analysis will use criminal data and spatial data mining algorithms to test the theory, if predictive crime patterns exist in a community.

2. LITERATURE REVIEW

Geographic information throughout history has supported crime analysis by identifying and developing spatial patterns. The methods may have changed over the centuries; however, the fact that there is a persistent relationship using geographic information to analyze crime has never changed. The use of maps in criminology traces its origins back to at least 1900 (Sheikh, et al., 2017). The original relationship started with pushpins on maps representing criminal activity, with the purpose of attempting to detect spatial criminal patterns. Even if this analysis did determine a pattern, the lack of a standardized distribution system during this era limited the effectiveness of this analysis (Santos, 2016). These analytical discoveries could trace origins back further than 1900, in Europe without a spatial archival or retrieval system, enabling others to access their research and facilitate in expanding spatial crime analytics (Santos, 2016). This created a cycle of repeated findings as each nation repeated existing research arriving at the same conclusion, an analysis system was needed (Santos, 2016). A scientific field of analysis with these flaws requires a change and this requirement facilitated the move from Geographic Information to Geographic Information Systems (GIS) (Sheikh, et al., 2017). Modern crime mapping and spatial analysis of crime are widely accepted as strong methods for the understanding of crime locations, because crime maps help investigate crime data and enhance perceptions of why crime occurs, but also where it is taking place (Chamikara, 2014). This statistical knowledge directly supports law enforcement intelligence by providing updated representations as crime changes across both time and space (Zahra, Ambreen, 2018). GIS-based crime analysis supports multiple fields of a criminal investigation. The process of using visual and statistical analysis of spatial crime locations to different types of crimes creates an opportunity to associate spatial and non-spatial data, enabling the creation of dynamic maps that assist the investigators in the analysis of crime locations (Usman, 2015).

2.1 Community and Crime

When conducting analysis into criminal behavior many factors have an impact. Some researchers theorize that the deciding factor is an amalgamation of time of day, location and temperature (Bernasco, Wim, Ruiter, and Block, 2017, Coccia, 2018, Vilalta, Carlos J, and Gustavo Fondevila, 2019). Others hypothesize locations associated with alcohol consumption act as an epicenter that attracts violent crime when observed through the colocation quotient (Ratcliffe, 2012, Roncek, Bell, 1981, Roncek, Maier, 1991). Both approaches operate inside the traditional theories on criminal behavior by applying a more impact analysis that focus on the four external influences, which are law enforcement, development, community and prevention (Tonry, and Farrington, 1995).

The community consist of a group of people living together and the infrastructure that make up their surroundings. Community is the most prevalent factor that make up our lives and the most underrepresented in crime research studies, due to its difficulty to define (Hope, 1995). Crime prevention can be facilitated through improvement of social environments, although the exact nature of how to define these changes is unclear (Hope, 1995). The goal was to prove that crime could become a less appealing choice, if other choices are present in a community or if a means of transit exist granting access to better opportunities (Hope, 1995). Scholarship has focused on the notion that changing the community has the potential to change the behavior of people that live within that community (Tonry, and Farrington, 1995). The reason the analytical focus has shifted to community development is that criminal activity was determined to be a predictive side effect of anti-social behaviors (Tonry, and Farrington, 1995). Studies in high-crime communities' have suggested that crime clusters at discrete locations leave many city blocks or areas relatively crime-free (Schnell, et al., 2017). These findings support the notion that community planning and design are major contributors to population safety and the density of crime present in a community (Kamal, et al., 2018). A large part of community development is the prevalence and improvement of educational institutions. Nordin hypothesized during a study that increasing the eligibility of higher education opportunities, could facilitate a decreased rate of property crimes and violent crimes due to the elimination of inactivity and idleness, which are two of the known causes of crimes in young adults in Sweden (Nordin, 2018). This idea directly relates to the creation of infrastructure in these communities often referred to as revitalization. Community revitalization can reduce crime in communities, because it seeks to eliminate the socioeconomic conditions that lead to the existence of crime (Hernandez et al., 2017). Hernandez, Arelys, Deryol, Ozer, and Engel study, concluded that in a community where revitalization projects included schools, it coincided with a reduction of violent crime throughout the area (Hernandez et al., 2017). They did acknowledge that they were not able to study the phenomena completely, due to data availability, but the potential for expanded research exists (Hernandez et al., 2017).

After schools, the next section of infrastructure thought to affect crime is religious centers. Researchers in the past have dedicated a lot of attention to the relationship between religious centers and criminal attitudes from a psychological perspective (Adamczyk, et al., 2017). Religion provides a layered deterrent approach that directly affects crime on both individual and communal levels, as religious centers provide a continuous religious message on societal norms and this message influences the individual behavior of attendees as a byproduct, reducing the likelihood of committing crimes (Nicolae, 2017). Religion also attempts to create an individualized fear of divine retribution for wrongs committed in the community (Nicolae, 2017). Religious centers are also epicenters of socially imposed embarrassment within a community and create a sense of fear that could deter criminal behavior (Nicolae, 2017, Rubin, 2018). The community factors that religious centers can have a deterrent effect on crime only if a majority of the community attends. Religious centers may have a negligible effect on crime in an atheist community; the deterrent effects have been studied socially, not spatially, which provides an opportunity for further development (Nicolae, 2017, Salvatore and Rubin, 2018).

The value of neighborhood parks added to the community has been a continuous question among researchers when it comes to its impact on criminal activity. This contention exist, because parks are a publicly owned resource and at the same time belong to no one. This dual ownership creates a situation where there is little individual investment and parks become susceptible to undesirable criminal activity (Groff, McCord, 2012). Even when scholarship examines the association between parks, tree canopy, and crime, it was determined, no significant association could be determined on parks and crime even though tree canopy could have a direct effect on crime (Schusler, et al., 2018). Conversely, parks create centers of community interactions and this allows for the strengthening of bonds between communities that will deter criminal activity (Groff, McCord, 2012).

In addition to the strengthening of community bonds, parks can assist in deterring crime by providing informal surveillance (Groff, McCord, 2012). Informal surveillance is an aftereffect of increased presence of people using the recreation facilities that parks have available. Parks with a higher diversity of features like walking trails, exercise equipment, and playground equipment can provide community surveillance for vast periods during the day and achieve an informal policing-like effect (Groff, McCord, 2012). This informal surveillance policy is a documented theory; very few studies have actually targeted parks when assessing crime density. Most studies assign parks into the same category as non-residential land use (Groff, McCord, 2012). A study of crime in Chicago revealed that the implementation of a greening project that converted vacant empty lots into parks preceded a significant decrease in criminal behavior (Brandon, et al., 2018). Researcher observations recorded that recreation facilities, like parks maintained by the community, could provide a higher level of deterrence for criminal behavior, the antithesis that parks when not maintained attract criminal behavior (Brandon, et al., 2018).

The last part, which pertains to the community analyzed for its literary relationship to crime is public transportation. As cities and metropolitan areas continue to expand, public transportation become vital to sustaining connectivity among its residents. Public transit generates crime, because they create a consistent schedule that criminals can monitor (Gallison, Andresen, 2017). Other researchers noted that there was no change in criminal behavior, due to the operation or maintaining of public transportation (Ridgeway, MacDonald, 2017, Qin, Xiaoxing, and Liu, 2016). Ridgeway and MacDonald encouraged future researchers to take this analysis at street level to evaluate attraction and repulsion of transportation centers (Ridgeway, MacDonald, 2017). The reason public transportation plays such a big part in crime analysis is as a service it connects multiple communities providing opportunities (Gallison, Andresen, 2017). Interconnectedness is a tangible value to society, but does it come at a cost of increasing crime and spreading fear (Spicer, Song, 2017). When conducting analysis into crime, people's perception plays a large part in the analysis and it was discovered that regardless of impact; people maintained a negative perception on the effects of public transportation on crime (Spicer, Song, 2017). Spicer and Song's research demonstrated that a properly designed transit hub could have positive effects on the surrounding community reducing criminal behavior, though this theory has not been fully investigated (Spicer, Song, 2017). The present narrative would indicate that a relationship between public transportation and crime exists (Stucky, Smith, 2017). To define this relationship, a determination is required to see if public transportation is an attractor or an impediment to criminal behavior.

The traditional solution to crime analysis is hotspot policing. But current research demonstrates it is a time-gated solution and often backfires (Barak, Partridge 2017).

Eventually, offenders can and will start too systematically and accurately predict the temporal and spatial pattern of police patrolling hotspots rendering these patrols ineffective (Barak, Partridge 2017). Dispersion is another logical unintended side effect of hotspot policing; in this case, the constant police patrols encourage criminals to seek other locations to commit crimes (Chillar, Darwve 2018). The long-term ineffectiveness of hotspot policing; over time combined with the potential of crime dispersion suggest the need for other techniques to prevent criminal behavior (Barak, Partridge 2017) (Chillar, Darwve 2018).

2.2 Crime Clustering

Researchers have examined criminal behavior over the years using numerous techniques and scientific approaches. These approaches include regression of coefficients applied to observe if substantial variation exists between times when crimes are committed (Bernasco, et al., 2017). Some researchers implemented a two-step process of spatial aggregation and linear mixed models to provide support for the spatial variability of violent crime in Chicago (Schenll, et al., 2017).

Visualization has become the backbone of modern-day crime analysis and clustering crime data is an approach that seeks to organize crime data into logical visual groupings (Samiullah, et al., 2017). Cluster visualization is a discovery tool used to reveal associations and structure in data that is not prevalent when raw data is analyzed (Gupta, Kaur, 2017). These associations when established make determinations on formal classification schemas or statistical models that represent patterns in a population (Gupta, Kaur, 2017). A common analysis used for clusters in criminology is Hotspot analysis.

Hotspot analysis identifies spatial clusters of statistically significant rates of crime occurrence (Sheikh, et al., 2017).

It is impossible to predict crime precisely even with analytical means due to the variety of sociological unknowns; however, there is the potential to predict the probability of occurrence through spatial means (Vaidya et al, 2018). Research achieved this by identifying the environmental conditions required to trigger specific types of crimes (Vaidya et al, 2018). Multiple researchers have supported this analytical approach by comparing and contrasting multiple environmental features and phenomena (Coccia, 2018, Ratcliffe, 2012, Bernasco, et al., 2017). In criminal terminology, a cluster is a group of crimes in a geographical region often referenced as a hotspot for crime (Vaidya et al, 2018). When applying the term clustering in the geospatial context, it references a group of similar data points (Nath and Varan, 2006, Athman, et al., 2015). When seeking to define newer patterns or detecting unknown patterns in data, clustering data mining techniques work better (Borg and Boldt, 2016).

2.3 Crime Pattern Analysis

Quantifying the spatial relationship between geographical entities and their neighbors is a common spatial topic (Han, et al., 2018). Tobler's First Law of Geography states that 'all attribute values on a geographic surface are related to each other, but closer values are more strongly related than are more distant ones' (Tobler, 1970). Research into numerous fields demonstrated that colocation patterns are prevalent in many aspects of organized societies. Spatial analysis of industrial development and spatial distribution has proven that industries seem to engage in a form of colocation called co-agglomeration

(Arbia, et al., 2008). Researchers' observed this phenomenon spatially when looking at food sources and housing types, verifying a spatial colocation pattern (Leslie, et al., 2012).

There have been consistent studies using colocation pattern mining to reveal the effects of liquor procurement locations and crime (Roncek, Bell, 1981, Ratcliffe, 2012). These studies have focused on defining the relationship between the number of liquor procurement locations and the number of crimes that occur on a block. Some studies established a connection between the numbers of liquor procurement locations, along with an increase in violent crimes (Roncek, Maier, 1991). The application of colocation studies on crime was not just limited to liquor procurement. Colocation analysis has proven that drug corners operated by multiple gangs experience more criminal activities than drug corners controlled by a single gang, establishing a detectable association (Ratcliffe, Taniguchi, 2008). This form of analysis is demonstrating a colocation pattern that exists between moneylenders and violent crimes, proving a persistent exchange of money, attracts criminal elements looking to exploit the weakness in cash exchanges (Kubrin et al., 2011). All of these studies focused on spatial features and their colocation with criminal activity, this field of pattern analysis is Rational Choice Theory analysis. Rational Choice Theory analysis seeks to explain why some places and targets within those areas are more likely to be victims of crime. This establishes the basis for creating trends of why some places are preferred over others using the central premise that offenders will minimize risks and maximize profits (Vilalta and Gustavo, 2019). Data mining colocation pattern analysis is a tool to precisely analyze criminal trends, but as the incidence and complexity of crime increase, human errors occur and analysis time increases dramatically. These time lags allow criminals more time to destroy evidence and escape arrest before a pattern of activity can be established (Chen, et al., 2004).

2.4 Crime Density Significance Testing

Tests for significance and criminology studies have a relationship, because as researchers seek to understand the nature of crime, they often attempt to link it to the surrounding geography. This geographical linkage created the concept of "Geography of Opportunity" which suggests that where individuals live, also affect their opportunities and life outcomes (Galster, Killen 1995). Geography influences social networks and frames individual development, thereby influencing the probability of committing a crime (Rosenbaum, 1995). T-test for significance provided the foundation for the relationship significance observation (Rosenbaum, 1995). In Rosenbaum 1995, used a T-test to demonstrate how relocation from a city to suburbs influenced crime in 1989, by contrasting population differences to prove the significance of a community in developing youths' informative years. In 2003, researchers applied a T-test to verify crime-forecasting analysis in an attempt to predict certain types of crimes to expand on targeted policing and hotspot analysis (Gorr, et al., 2003). The goal of a T-test is to determine whether a significant difference between the mean of two groups exist. Rémi Boivin used this tool to demonstrate the spatial relationship of crime and visiting populations (Boivin, 2018). This study proved that there is a definable significance value for crime in areas with higher visiting populations' because; they experience a definitive increase in crime versus areas with routine activity by a residential population (Boivin, 2018). Researchers' applied a T-test for significance in criminal studies to establish statistical significance for events and provide support for a hypothesis (Coccia, 2018). Coccia applied a T-test to compare the arithmetic means of different temperate zones and homicide to test if there is a significant difference between temperatures (Coccia, 2018). This application of the T-test demonstrates a relationship between temperatures and violent crime providing a partial explanation for why violent crime in society increases during times of high temperatures (Coccia, 2018). T-test for significance established a relationship with supporting crime analysis, because of its ability to analyze means and provide support for hypothesis is invaluable to crime research opportunities.

In summary, research papers studying criminal behavior in our society analyze infrastructure features that contribute to the presence of crime in a region. Often this association links violence with alcohol and burglary with places where cash frequently exchanges hands (Ratcliffe, 2012, Kubrin et al., 2011). There is research that demonstrates infrastructure features can contribute to an increased crime presence or the perception of increased crime. This abundance of evidence indicates that the inverse is also possible for infrastructure features to have a counterbalancing effect and reduce or completely repel criminal behavior. Since researchers have primarily focused on attractors when studying crime the sources that deter crime is widely unexplored and not prevalent in the current literature (Han et al., 2018). If attractors for crime truly exist, determining the optimal parts of infrastructure to support security and reduce criminal activity is the next logical step in the process for determining infrastructure as a deterrent (Boivin, 2018).

3. STUDY AREA, DATA, AND IMAGERY

3.1 Study Area

This thesis will focus on the city of Seattle, Washington which is located in King County and whose centroid is situated at 47° 36' 22.354" N 122° 19' 55.455" W with respect to the World Geodetic System of 1984 (WGS84) datum. King County encompasses an area of approximately 2,126.1 sq. miles with the city of Seattle and its suburbs 83 sq. miles (About Seattle - OPCD | Seattle.Gov, 2019). Seattle's existing land use has been extrapolated into seven categories provided by King County Department of Assessments with single-family homes making up 49% of its land use, followed by parks and open spaces using 14%, which is closely trailed by major institutions, and public facilities at 11% (About Seattle - OPCD | Seattle.Gov, 2019). Nearly all of Seattle's population, 97.5%, lives within ¼ mile of a transit stop with some level of service (About Seattle - OPCD | Seattle.Gov, 2019). The economy of Seattle, WA employs 2.02 million people. The largest industries in Seattle, WA are Health Care & Social Assistance, Retail Trade, and Professional, Scientific, & Technical Services (Seattle-Tacoma-Bellevue, WA | Data USA). The highest paying industries are Utilities, Professional, Scientific & Technical Services, and Information (Seattle-Tacoma-Bellevue, WA | Data USA). Between the years of 2013 and 2016, Seattle experienced an 8.6% population increase (Bureau, U. S. Census, 2019). Even with all these economic activities and a median household income of $82,133, reported crimes in Seattle has continued to increase annually from 2013 to 2016 (Seattle-Tacoma-Bellevue, WA | Data USA) as emphasized by Figure 1 below. Seattle's abundance of diverse infrastructure in the immediate surroundings, coupled with its persistent reported crime data, provides a unique environment to conduct a study on the significance of infrastructure and crime.

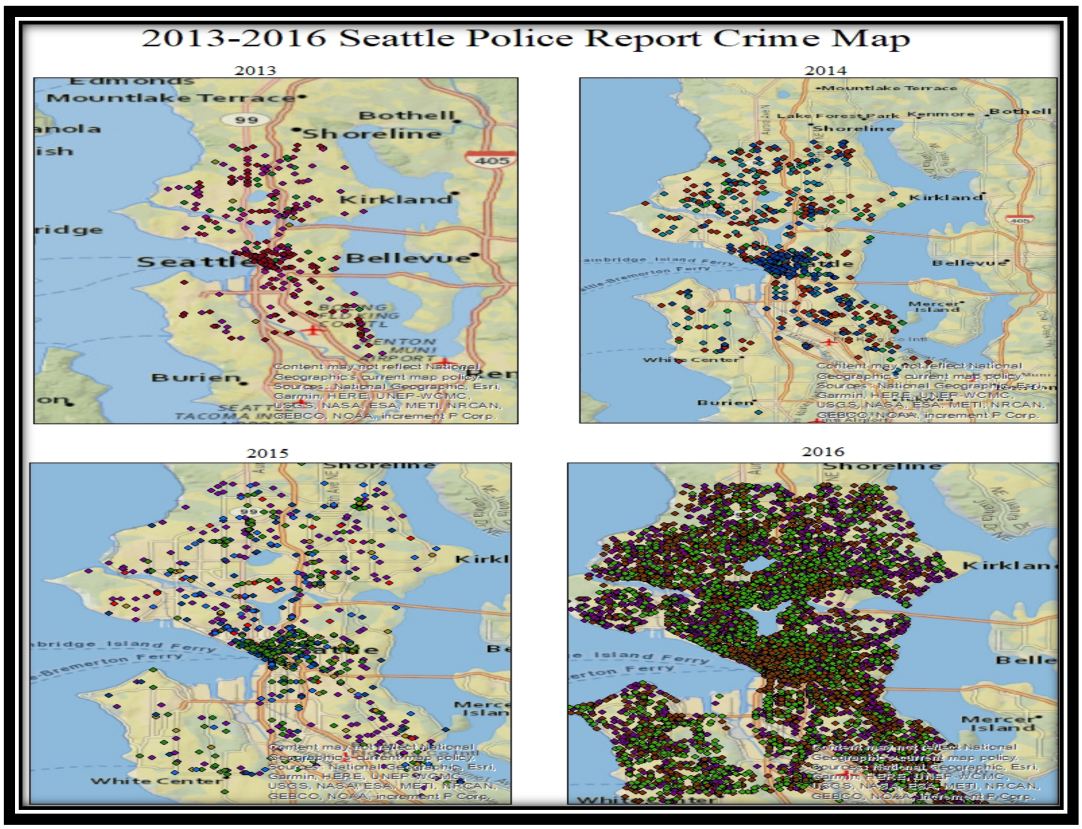

Figure 1 2013-2016 Police report Map

3.2 Data

This thesis on crime pattern analysis relies on multiple data sources divided into three categories; the first data source is imagery and census data, the second data source is criminal activity data, and the third data source is infrastructure data. All of these data categories are required to create a complete representation of the city of Seattle and serving as a temporal model that will enable the discovery of a conclusion on the possibility of significance between the events contained within each crime category and its surrounding community and persistent pattern of criminal activity.

3.2.1 Imagery

This study used imagery data supplied by the ArcGIS geographic information system and served as a base mapping and outlining the city of Seattle. National Geographic World Map disseminated by ESRI and developed by National Geographic reflects the distinctive National Geographic cartographic style in a multi-scale reference map of the world (National Geographic World Map, 2019). The map incorporated data from a variety of leading data providers, including Garmin, HERE, UNEP-WCMC, NASA, ESA, USGS, and others (National Geographic World Map, 2019). The land-use features pre-rendered in the National Geographic World Map, provided administrative boundaries, cities, protected areas, highways, roads, railways, water features, buildings, and landmarks, overlaid on shaded relief and land cover imagery for added context (National Geographic World Map, 2019). The map includes global coverage down to ~1:144k scale and detailed coverage for North America down to ~1:9k scale (National

Geographic World Map, 2019). The National Geographic World map below displays the base map imagery used for Seattle in this study.

Figure 2 National Geographic World Map Seattle

Washington Geospatial Open Data Portal database provided and maintained the census blocks database (SAEP Census Block Groups, 2019). Each feature layer in the database contained the estimated population from the years 2000 through 2018 and a polygon identifying the boundary of the census blocks with the corresponding latitude and longitude given in WGS84 coordinates. The Seattle Census block figures show the Seattle Census Block database extraction transformed into an overlay and spatially reference over the Seattle imagery. This inclusion completed the creation of the city of Seattle model used in this study.

Figure 3 Seattle Census Blocks

3.2.2 Crime Data

Seattle Washington Open Data Portal provided the criminal activity data used to support this analysis. This data portal is an open-source that provides spatial information about the city of Seattle. Part of the information included in the data portal is Seattle

Police Department Police Incident Reports. This repository is a living data source that updates every 6 to 12 hours as new police reports are processed (Seattle GeoData, 2018). The repository contains each police report organized by category and contains the adjusted spatial coordinate system for the event listed in the reports. The location adjustment when tested is a small radius shift to protect the rights and privacy of individuals providing this report; while it did shift the core report, the degrees of difference were not enough to affect the outcome analysis using the data. This small adjustment in location data is geomasking. Geomasking provides privacy protection for victim addresses, enabling sensitive data to be mapped (Allshouse et al., 2010). Fields in the data, reflected geomasking occurred, but there was no direct linkage to the geomasking algorithm that Seattle Washington Open Data Portal applied.

In Seattle between the years of 2013 and 2016, the Seattle police department filed 86,383 crime reports. Of these crimes, 45,782 fell into the eight crime categories analyzed in this study (shown in Table 1). The 2013 through 2016, Crime Density in Table 1, illustrates the number of police reports filed by crime type per year in Seattle and the density per square mile of each crime when contrasted within the area of Seattle. A pattern that emerged is the number of reported crimes in the city of Seattle continues to rise every year. The only exception to this pattern rule is homicide, which decreased in 2015. Crimes like Assault, Burglary, Vehicle Theft, and Car Prowling increased exponentially with Burglary experiencing a 96.11% increase between the years of 2015 and 2016 alone.

Table 1 2013 through 2016 Crime Density Table

	Assault	Bike Theft	Burglary	Car Prowling	Homicide	Narcotics	Robbery	Vehicle Theft
2013 Total Crime	133	13	96	57	10	145	22	42
2013 Crime Density per sq. mile	(0.1964)	(0.0191)	(0.1417)	(0.0841)	(0.0147)	(0.2141)	(0.0324)	(0.0620)
2014 Total Crime	205	23	373	107	20	122	50	197
2014 Crime Density per sq. mile	(0.3027)	(0.0339)	(0.5508)	(0.1582)	(0.0295)	(0.1801)	(0.0738)	(0.2909)
2015 Total Crime	306	94	464	196	10	191	94	134
2015 Crime Density per sq. mile	(0.4519)	(0.1388)	(0.6852)	(0.2894)	(0.0147)	(0.2820)	(0.1388)	(0.1978)
2016 Total Crime	5122	1065	11916	10700	133	2594	3174	7982
2016 Crime Density per sq. mile	(7.5641)	(1.5727)	(17.5975)	(15.8017)	(0.1964)	(3.8308)	(4.6873)	(11.7878)

3.2.3 Infrastructure Data

The next category of data required to build this analysis used in the spatial study was Infrastructure Data Category. This category of data was composed of five major types of infrastructure; schools, religious centers, parks, bus stops, and emergency stations. ArcGIS open hub data and Data.Seattle.Gov provided the data for religious centers and schools (ArcGIS Hub, 2018, City of Seattle Open Data Port, 2018). For religious centers, the data contained multiple types of religious centers and was not limited to just one particular faith or denomination. This diversity of places to worship creates the best opportunity for community study, while accounting for the neighborhood ethnic demographics. The educational institution data consisted of different levels of education. This diversity provided better coverage of multiple age groups. Diversifying the datasets in religion and education reduces the possibility of a certain age demographics and ethnic background will be unaccounted for in this study.

The next data sets used for the community analysis portion of this thesis was parks and bus stops. This feature data came from ArcGIS open hub data and Data.Seattle.Gov respectively, both are open data sources with no usage restrictions listed (ArcGIS Hub, 2018, City of Seattle Open Data Port, 2018). Both of these provided a massive list of parks and bus stops throughout the Seattle, Washington area. Parks are open source and unmanaged forms of community infrastructure. The term, unmanaged infrastructure means, these facilities are available for public use with no oversight by a centralized body. The lack of centralized management means, they have no events or guaranteed attendance. This differs from bus stops where people gather at specified times, providing a widespread cultural mixing bowl throughout the community, providing a managed public service. Bus stops provide the opportunity for travel across multiple communities, so the potential for them to have a cultural impact is much higher than stationary facilities like parks. Parks are places were unplanned gathering and interaction among groups of people occur. Parks provide a chance for physical activity, but there usage and impact on a community is questionable. Even for maintained parks, there is no set schedule for congregation and interaction among attendees.

The last part of infrastructure is the control feature that tested the accuracy of the results. In this study, the control is local emergency stations and the analysis of crime density in the surrounding environment. King County GIS Data provided the emergency stations information and the data was extrapolated from the common point of interest table. This data table was open source with no usage restrictions and provided a searchable list of all emergency stations in the Seattle, Washington area (King County GIS Data Hub - King County, 2018). Emergency Stations data type consists of Fire Rescue stations and Emergency Management stations throughout Seattle. Emergency stations serve as a control group; based on the assumption they are likely to be more significant on crime density, because of their association with government and potential ties to law enforcement. The Community Infrastructure Density Table outlines the amount of infrastructure and density of each infrastructure type present in Seattle during this study. The Community Infrastructure Density Table below demonstrates the most prevalent type of infrastructure, is parks having 518 locations throughout Seattle while the least prevalent is emergency stations at 39 locations.

Table 2 Community Infrastructure Density Table

	Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
Total Infrastructure	222	518	250	163	39
Infrastructure Density per sq. Mile	(0.3278)	(0.7649)	(0.3692)	(0.2407)	(0.0575)

4. ANALYSIS METHODS

This thesis will address two research questions about crime by analyzing crime data, community infrastructure, and census block data from 2013 to 2016. These are: (1) Does community infrastructure have a significant effect on overall crime density in its surrounding environment? (2) Is it possible to use crime occurrence in census blocks as antecedents to establish association rules that can predict the consequent crime patterns?

4.1 Significance Testing Methodology on overall crime density

When analyzing criminal activity in a region, it is difficult to determine root cause; because, causation is more of a social physiology problem and the root cause can vary between criminal events, creating an inconsistency. This inconsistency is limiting for most fields, conducting analysis into criminal patterns, which serves to enhance the potential for geospatial pattern studies into criminal activity. This new potential exists because geography focuses on the ability to look at influences in a region that goes beyond sociological sciences, by focusing on spatial data observations for new avenues of explanation. By systematically applying geospatial scientific methods, there can be a determination on how the external features in an environment influence criminal behavior and their significance.

To facilitate this analysis, infrastructure facilities are going to be a centroid in an attempt to understand the density of crime around these locations. This analysis is going to apply two principles of significance; the first is the theoretical significance and the second is the analytical significance (Ratcliffe, 2012). The concept of proximity based on the theoretical significance of infrastructure facilities in a community and their ability to produce a definable effect can be associated with a reduction of crime density around these facilities. The analytical significance of this theory is with the appropriate methodology combined with a focus on point density, a deterministic analysis can be achieved representing the impact of facilities on criminal activity in a region.

4.1.1 Building Buffers

The creation of crime clusters, show there is a visible representation of how criminal activities interact. The next step in attempting to determine the effects of infrastructure facility colocation on criminal activity is to build concentric buffers around the infrastructures. The study will achieve this by establishing an initial buffer distance of a quarter-mile to identify if any crime variables are collocated within a range of infrastructures and the surrounding neighborhood. This buffered distance band is attempting to represent one city block around the infrastructure with the purpose of identifying and isolating crimes that happen near or inside the infrastructure facilities. The next interval of a buffered distance is one-eighth mile. The one-eighth mile buffered distances covered by this represents adjacent streets and city blocks closer to the infrastructure. These areas have the potential to be directly impacted by infrastructure facilities due to closer proximity. The next distance band in our study is the one-sixteenth mile distance band. It reflects the midway point of the distance bands used and represents the edge where the transition begins from nearby streets and buildings to the immediate area around the target facility. The next distance buffer is one thirty-second mile distance band that represents the surrounding exterior of most facilities. The final buffered distance interval is a range band that will cover one-sixty-fourth mile radius, representing the interior of the facility and seeing if a crime is occurring within the infrastructure facility. The Distance Band Visualization in Figure 4 shows a visual representation of the range bands applied to a church in Seattle. This spectrum of buffered ranges creates a banded radius of buffers around the infrastructure allowing for a more complete representation of how these identified facilities affect crime in this area.

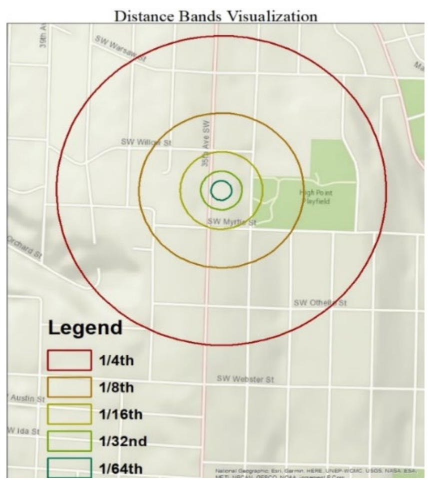

Figure 4 Distance Band Visualization

Ratcliffe presented the methodology of applying concentric buffers in his research paper "The Spatial Extent of Criminogenic Places: A Changepoint Regression Of Violence around Bars" in 2012. This new methodology of applying concentric buffers for analysis on crime took inspiration from Ratcliffe's research (Ratcliffe, 2012). Campbell a researcher conducted analysis on this method of crime analysis used by Ratcliffe, identified as Circle Theory. Campbell's research challenged the overall effectiveness of Circle Theory due to its susceptibility to outliers and circle overlap when the offender is the centroid of Circle Theory (Campbell, 2019). Ratcliffe's implementation of Circle Theory was different when studying violence around bars; he used concentric buffers to establish a distance for violent acts that take place inside or in the immediate vicinity around bars by using bars as the centroid. Implementing the same methodology, this study attempts to assist in the determination of the colocation of infrastructure and criminal activities with alterations. The alterations occurred in the creation of distance bands where Ratcliffe's distance bands focused on bars and his only target activity was violence in areas contained in his buffer were smaller, because he was trying to approximate inside the bar, the parking lot or adjacent streets. The focus of this research is community-based, the buffers must be expanded to encompass a perceivable community, which coincided with a buffered distance increase expanding the range of values from one sixty-fourth mile up to one-fourth miles.

4.1.2 T-test to Determine Significance of Infrastructure

This study uses the T-tests Statistic for Hypothesis testing in order to prove the existence of a colocation relationship. A T-test is a statistical approach that examines the mean value of multiple variables to determine if they are statistically different from each other and have a relationship. T-test define the relationship between different infrastructures and crime at various predefined distances (Gorr et al., 2003).

The multiple buffered distance sizes starting at one-fourth mile and decreasing by half the previous distance are testing areas to determine the significance infrastructure is having on crime density. A uniform application of this methodology was applied to every crime category included in the initial analysis and represented in a T-table based on the crime type that is being examined for a relationship.

With the creation of T-test tables for criminal variables and infrastructure, this study requires baseline observation values and the infrastructure T-test tables can determine, a probability value that will determine if the effect is truly relatable (Coccia, 2018). Applying the T-test statistic to infrastructure crime values by calculating a T-value explained in section 4.1.3 and then determining a hypothetical mean value that represents the total crime density by type will facilitate in determining reliability. The formula for calculating the hypothetical mean for this study used the summation of all crime values of that crime type, represented by $\sum m$ divided by the total number of census blocks represented by V and divided by 2.59 to convert from squared kilometers to squared miles.

Equation 1 Hypothetical Crime Density Mean

$$\mu = \frac{(\frac{\sum m}{V})}{2.59}$$

When analyzing the infrastructure facility, T-test results with the scientific objective is to see how the T-value corresponds to the hypothetical mean value of crime density at the pre-established distance band. This analysis will be the defining proof providing a probability of the effectiveness of infrastructure on criminal behavior in its surroundings at each buffered distance.

4.1.3 Application of the T-test Statistic and P-value

The T-test statistic will depend on the previous defined distance buffers in section 4.1.1 to determine the average amount of criminal variables of the same type that collocate within that spatial region for each infrastructure facility. The analysis of crimes that occur within the predefined buffered distances of a section of the infrastructure and analyzed against the total amount of that type of crime present within the city of Seattle during that same year. A metric count of crimes within each buffered distance and all the crimes citywide will be collected and averaged independently to determine the mathematical mean, standard deviation, and variance. The mean, standard deviation and variance values processed through One Sample T-test formula displayed in Equation 2 providing a T-value. Using a T-value with the T-Distribution enables the finding of the probability of crimes occurring within infrastructure distance bands.

Equation 2 One Sample T-test

$$t = \frac{\overline{x_1} - \mu}{\frac{s}{\sqrt{n}}}$$

In this formula, $\overline{x_1}$ represents the sample means from the buffered distance bands of the specified crime type μ is a hypothetical mean, which is crime type density value defined in section 4.1.2. This formula uses s to determine the sample variance, derived from the crimes contained in each buffered distance band around a portion of the infrastructure. The variable n is the sample size from within the buffered distance bands of targeted infrastructure facilities of the specified crime type studied. Once these formula components are derived, the next step is to determine the t-value through the use of all previously mentioned components and the T-test formula in Equation 1.

The application of the previous formulas resulted in the generation of a t-value that is reflective of the difference between criminal behavior around infrastructure and the city of Seattle. Finding the t-value creates the opportunity to do a statistical significance test to determine the calculated probability or p-value. A p-value represents the probability of finding the observed results, when conducting hypothesis testing (P Values (Calculated Probability) and Hypothesis Testing – StatsDirect, 2018). The p-value when analyzing criminal behavior within the distance bands is conducting a test where the likelihood of results is occurring from random chance. For this analysis, there are two hypotheses; the first is infrastructure affects crime at different distances; this is the alternative hypothesis and the second hypothesis that crime is completely random and the infrastructure is not affecting crime within the established distance bands, this is the null hypothesis. When conducting the p-value analysis a higher p-value validates the hypothesis, that criminal behavior is completely random within the established distance buffers. A lower, p-value indicates a significant probability that infrastructure in the area is having a direct effect on crime within the distance bands.

4.2 Association Rule Mining through the Apriori Algorithm

Past researchers have demonstrated crime can have a prevalent pattern through the creation of heat maps. These maps asserted that spatial clusters of crimes observed in the previous week, would persist into the next week, creating spatial hotspots (Hua and Brown, 2003). This research phenomenon has supported using Pattern Analysis (PA). PA's analytical approaches build the foundation for determining if spatial relationships exist, but what are the principles of the relationships of causation, and how does it facilitate in the development of related event prediction of algorithms. This study is going to take a different approach to hotspot analysis by combing crime data with census blocks to develop association rules for how crime attracts other crimes in the city of Seattle. This will be a more predictive data model than the standard hotspot analysis, focusing on identifying consequential criminal activity, rather than just indicating areas that have large amounts of crime. This analysis will be using the Apriori algorithm to create rulesets and patterns from the established data looking for persistent rules that span multiple years.

4.2.1 Crime Itemset Creation

To apply Apriori algorithm to the existing geospatial data, required some reprocessing of the original crime data, because the data needed to transform from a geospatial database to geospatial itemsets organized by census block data. To create an itemset, every police report in Seattle's database was required to be associated with a census block. Applying the mapping software's Spatial Join by location, to identify the census blocks, where each crime occurred, creating a database field linking the crime to the census block, established this association. If a crime existed on the census block boundary, the mapping software would assign it to the census block that it is closest in distance. Once all crimes were associated with a census block, another spatial database review was required to create the spatial itemsets of crimes. This review was a binary search of the geodatabase, which constructed spatial itemsets by going through all the census blocks and identifying if a certain type of crime was present for the year analyzed. An example could be; a census block in Northern Seattle may only contain two of the eight studied types of crime for the year, therefore, that census block itemset would consist of two items while another could consist of all eight crimes in one census block. The Apriori algorithm is an objective way of defining rules of association, because of its through approach to data mining. The 2013 Crime Itemset Example in Table 3 provides an example itemset extracted from 2013 geodatabase of crimes reported in Seattle. The ID field represents the census block ID number and the crime itemset represents the crimes that were present in that census block during that year.

Table 3 2013 Crime Itemset Example

Census Block ID	Crime Itemset
8002	{Assault, Homicide, Narcotics}
5005	{Robbery, Homicide}
6003	{ Assault, Robbery, Car Prowling, Bike Theft, Homicide}

Each itemset generated details about what crime types occurred in each census block for the year, omitting the crime types that did not occur in the census blocks. This study will be generating itemsets for every census block for every year of this study. This process generated between 182 itemsets in 2013 to 500 itemsets in 2016. The creation of itemsets enables the data processing through Apriori algorithm in order to generate association rules.

4.2.2 Association Rules

Association rule mining remains a very popular and effective method to extract meaningful information from large datasets (Rathee et al., 2016). Association rule mining tries to find possible associations between items in large datasets using frequent patterns and generated rules. The Apriori algorithm is one of the earliest proposed frequent pattern generation algorithms and remains a preferred choice due to its ease of implementation and scalability when working with large datasets (Rathee et al., 2016). In the past, to define relationship rules, the Apriori algorithm has been applied in a study conducted in 2017 by Sevri, Karacan and Akcoyol. The Apriori generated association rules about burglary location, weapons used and victim ethnicity with 0.954 levels of certainty in the pattern (Sevri, et al., 2017). This study is going to expand on Sevri, Mehmet, Karacan, and Akcayol 2017 research, but rather than targeting one specific type of crime and racial demographics, it is going to attempt to derive Association rules for eight crimes types and how they propagate together throughout Seattle.

Association rules are a representation of the likelihood that variables in a study will happen around another variable in the study. This study is trying to establish rules for crime occurrences throughout Seattle and achieve this by applying the association rules' three metrics to better define the relationship between the eight crime type variables. The metrics are support, confidence and lift.

4.2.3 Support

Support is the percentage of task-relevant data transactions for which a perceived pattern is true (Harikumar, et .al 2016). Consider a 2013 crime database with *itemset1* = {X} and *itemset2* = {Y} in this example X represents Vehicle Theft and Y represents Car Prowling. For this explanation assume that there are far more police reports containing X than those containing Y. *Itemset1* will generally have higher support than *itemset2*. For bigger itemsets, lets introduce a third variable Z to represent narcotics the logic is similar to *itemset1* = {X, Y} and *itemset2* = {X, Z}. For this example, many transactions have both X and Y in the dataset, but not X and Z. In this case, *itemset1* will generally have higher support than *itemset2*. The formula for support is listed below in Figure 2, where X, Y are itemsets, T is a set of transactions or reports containing the itemsets in the database and lastly, t is the portion of transactions that contain itemset X:

Equation 3 Support Formula for Association Rule Mining

$$Support(X) = \frac{|\{t \in T; X \subseteq t\}|}{|T|}$$

4.2.4 Confidence

Confidence is the measure of certainty associated with each discovered pattern (Harikumar, et .al 2016). In the following example, the variables X and Y are going to represent Vehicle Theft and Car Prowling respectively. Therefore, to determine the confidence for itemset {X, Y} in 2013, there must be an analysis of all the census blocks containing{X} that also had {Y}. Since crime X is routinely located with crime Y, this will have a high confidence rule. Confidence is the conditional probability of occurrence of consequent given the previous states. The confidence formula is in Equation 4 below:

Equation 4 Confidence Formula for Association Rule Mining

$$Confidence(X \rightarrow Y) = \frac{Support\ (X \cup Y)}{Support(X)}$$

4.2.5 Lift

Lift of rule is the probability of observed support to expect if {X} and {Y} were independent (Harikumar, et .al 2016). If the value of Lift for X and Y equals one, then this indicates the values are independent of each other, and no rule can be deduced for these two events. If the lift is, less than one it means that the items are a substitute for each other's presence and one has a negative effect on the presence of the other. While a lift of greater than one means that, the values are dependent on one another and allows for the creation of rules to predict potential occurrences. The lift formula is in Equation 5 below:

Equation 5 Lift Formula for Association Rule Mining

$$\boldsymbol{Lift(X \rightarrow Y) = \frac{Support\ (X \cup Y)}{Support(X) \times Support\ (Y)}}$$

4.2.6 Apriori Algorithm

The Association rules for the existing crime data in this study come from the application of Apriori algorithm. Agrawal and Srikant developed the Apriori algorithm in

1994 for mining frequent itemsets for association rules (Agrawal, Srikant, 1994). The Apriori algorithm uses prior knowledge of frequent itemset properties to employ an iterative search for associations or patterns in the data (Han, et al., 2011). The Apriori has become one of the most prominent algorithms for mining frequent itemsets for generating association rules (Harikumar, et .al 2016). It operates on the principles that subsets of frequent item are frequent itemsets and the supersets of infrequent item are infrequent itemsets (Harikumar, et .al 2016). Researcher Yabing, in his 2013 research paper called "Research of an Improved Apriori Algorithm in Data Mining Association Rules" identified that the Apriori algorithm has a few of the weakness that typically plague other frequency data mining techniques, such as multiple table scans, storage, and searches of a large number of candidate sets for frequent itemsets (Yabing, 2013). These weaknesses are minor when considering that the Apriori algorithm considers every attribute irrespective of them being independent or dependent on each other (Maolegi, Arkok, 2014).

To define the association rules for criminal activity the Apriori algorithm is going to employ an iterative search (Yabing, 2013). In this algorithm, each census block crime itemsets are candidate items referred to as C in the Pseudo-code, while k represents the size of the itemsets. The first step in this process is finding the frequent 1-itemsets by scanning the database to accumulate the count for each item, and collecting those itemsets in L1. The next iteration of the algorithm uses L1 to find L2, the set of frequent 2-itemsets, which finds L3, and so on, until no more frequent k- length itemsets exist.

The finding of each Lk requires one complete scan of the database. The entire Apriori algorithm in Pseudo-code in Equation 6 below:

Equation 6 Apriori Algorithm Pseudo-code

C_k: Candidate itemset of size k
L_k : frequent itemset of size k
L_1= {frequent items};
for (k = 1; L_k!=∅; k ++) do begin
    C_{k+1}= candidates generated from L_k;
    for each transaction t in database do
 increment the count of all candidates in C_{k+1}
 that are contained in t
L_{k+1}= candidates in $C_{k+1}$with minimum support value
end
return $\cup_k L_k$;
(Yabing, 2013)

The completion of the Apriori algorithm will identify all the potential frequent crime itemsets and define the support value for each (Sevri, et al. 2017). The formula for defining the support value is in section 4.2.3 for Association Rule Creation. The support number is a count of the number of itemsets containing the potential frequent items divided by the total number of itemsets. For an itemset to be a frequent itemset, a determination, using a pre-defined support value and itemsets support values are compared. If an itemsets support value is equal to the user predefined minimum support value or exceeds the minimum predefined user support, the itemset is frequent itemset and has association rule (Englin, Riley, 2015).

The final step in Apriori process is the verification of the confidence value reviewed in section 4.2.4. The Confidence Formula for Association Rule Mining provides a measure of certainty of the discovered pattern. The confidence value is the number of itemsets containing frequent items divided by itemsets containing just one value (Englin, Riley, 2015). Analysis of itemset confidence value and a user-defined confidence value occurs and if the itemset confidence value meets or exceeds the user-defined confidence value, the itemset can generate an Association Rule.

All crime census blocks in over four years analyzed in this study will undergo this analysis methodology. This analysis will use support values from ninety percent to one percent to ensure complete coverage, maintaining the highest possible quality of associate rule generation. The confidence value probability will apply the intelligence community standard of seventy-five percent. This principle was derived from Words of Probability written by Sherman Kent (Friedman, et al., 2016). Kent's research indicated that a possibility of seventy-five percent was probable and anything above ninety-three percent is almost certain to occur (Friedman, et al., 2016). This targeted application of the Apriori algorithm should assist and establish a basis, if any Association Rules based on the frequency of crimes occurring in Seattle. This could potential define what crimes attract or comingle with other crimes in the city of Seattle.

5. RESULTS

5.1 Crime and Infrastructure Significance Results

The results of the significance testing of crimes in Seattle from 2013-2016 with infrastructure, including their Means, Standard Deviation, T-value, and P-value are shown in the tables contained within this section. Mean values that are statistically significant with a P-value between .05 and .02 levels will be indicated with a single asterisk (*) within the table cellblock at the end of the mean. P-values that equal to .01 or less are statistically highly significant and will be indicated with a double asterisks (**) with the table cellblock at the end of the mean. In these tables, each cellblock contains the mean for each infrastructure type, located on the top and the standard deviation on the bottom in parenthesis showing the T-value, and P-value. The leftmost column lists the distance bands considered in this analysis. There were five buffered distances analyzed, however, only three-buffered distance bands are used in each table. The reason for this is one-thirty-second mile and one-sixty-fourth mile buffered distances contained virtually no crime for any of the infrastructure categories and the results were uninformative. Geomasking could have influenced why the results around one-thirty-second mile and one-sixty-fourth mile buffered distance are so uninformative. Geomasking protects the victim identity and those distances are closest to the infrastructure location so geocoding that information could compromise the victim's identity. The following section lists the results by crime type, noting the effects of various infrastructure categories in the remaining three distances.

5.1.1 Assault

The following section contains the results for the significance testing of assaults in Seattle, when analyzed by its colocation within the predefined distances around the infrastructure points. In 2013, bus stops and religious centers across all distances proved statistically highly significant when compared to the overall assault density rate of 0.1964, while parks only demonstrated statistical significance at one-eighth and one-fourth mile. Emergency stations showed statistical significance at one-fourth mile distance only. Schools demonstrated no significance across all distances, when compared to assaults crime density rate for 2013. The results demonstrated for one-eighth and one-sixteenth mile buffer around religious centers showed a significantly lower amount of assaults than the county average, although this effect is gone at the quarter-mile band. Averages were highest around bus stops and emergency stations, with schools having the lowest averages. Standard deviations for all cells were reasonably large compared to the mean values, indicating a large amount of variation within the distance-band.

Table 4 2013 Assault Density Significance per Square Mile

Assault Density per Sq. mile 2013		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean St. Dev T-value P-value	0.2839 (0.7847) 1.6622 0.0979	0.4237** (1.6686) 3.1004 0.0020	2.8022 ** (3.8939) 5.0964 0.0001	9.3277 ** (18.9001) 6.1683 0.0001	1.3047 * (3.1697) 2.1836 0.0352
$\frac{1}{8}$ *mi.*	Mean St. Dev T-value P-value	0.1657 (0.8552) 0.5314 0.5957	0.5233 ** (2.8125) 2.6276 0.0089	4.3184 ** (7.3310) 4.2451 0.0001	0.0187 ** (0.2387) 9.4697 0.0001	1.4025 (3.8088) 1.9777 0.0553
$\frac{1}{16}$ *mi.*	Mean St. Dev T-value P-value	0.1681 (1.4235) 0.2923 0.7704	0.4826 (3.5648) 1.8207 0.0720	4.1268 ** (10.1837) 2.8882 0.0055	0 ** (0) 0 0	0.9356 (3.2835) 1.406 0.1679
	2013 Assault Density per sq. mile			0.1964		
	2013 Assault Standard Deviation			(0.8031)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

In 2014, bus stops across all distances proved statistically significant when compared with the overall assault density rate of 0.3027. Schools and emergency stations only showed statistical significance at one-fourth mile. Parks only demonstrated statistical significance at one-sixteenth mile. Religious centers showed a statistical high significance across all distances except one-sixteenth mile distance. In 2014, schools at one-eighth mile demonstrated the lowest average for assault, while religious centers at one-fourth mile demonstrated the highest average for assault. Standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-band, with religious centers having the largest at one-fourth mile.

Table 5 2014 2014 Assault Density Significance per Square Mile

Assault Density per Sq. mile 2014		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi*.	Mean	0.5953 *	0.5688	4.0985 *	13.6558 **	1.2268 *
	St. Dev	(2.1804)	(1.7127)	(4.4100)	(31.9471)	(2.5702)
	T-value	1.9992	1.8670	4.4086	5.3364	2.2454
	P-value	0.0468	0.0625	0.0001	0.0001	0.0306
$\frac{1}{8}$ *mi*.	Mean	0.2900	0.6184	4.6383 *	0.7315 **	1.0129
	St. Dev	(1.4949)	(2.5348)	(6.3720)	(2.0548)	(2.7299)
	T-value	0.1252	1.7712	4.9551	2.6566	1.6248
	P-value	0.9005	0.0770	0.0001	0.0087	0.1125
$\frac{1}{16}$ *mi*.	Mean	0.3363	0.7722 *	5.2129 *	0.8362	0.6237
	St. Dev	(2.5953)	(4.9696)	(15.7070)	(3.6405)	(2.7179)
	T-value	0.1908	2.1213	2.3394	1.8538	0.4863
	P-value	0.8489	0.0344	0.0230	0.0656	0.6288
	2014 Assault Density per sq. mile			0.3027		
	2014 Assault Standard Deviation			(1.1766)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Bus stops and parks across all distances in 2015, proved statistically highly significant when compared to the overall assault density rate of 0.4519. Religious centers proved significant across all distances, demonstrating a particular high statistical significance at one-fourth mile distance band, while other distances only indicating a statistical significance does exist. Schools only displayed high statistical significance at one-sixteenth mile buffer distance. Emergency stations only demonstrated statistical significance at one-eighth mile. In 2015, religious centers contained both the highest and the lowest mean values for Assault with the highest occurring at one-fourth mile and the lowest occurring at one-sixteenth mile buffered distance. Standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-band values with religious centers having the largest at one-fourth mile.

Table 6 2015 Assault Density Significance per Square Mile

Assault Density per Sq. mile 2015		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ $mi.$	Mean	0.8005	1.0688 **	7.0055 **	29.6250 **	2.0642
	St. Dev	(2.7669)	(3.7360)	(8.5251)	(81.6735)	(5.2530)
	T-value	1.8773	3.3546	5.8545	4.5603	1.9168
	P-value	0.0618	0.0009	0.0001	0.0001	0.0628
$\frac{1}{8}$ $mi.$	Mean	0.9254	1.2548 **	10.6629 **	0.9191 *	2.4934 *
	St. Dev	(2.7669)	(5.6994)	(16.2957)	(2.8356)	(6.2696)
	T-value	1.0085	3.1846	4.7308	2.0974	2.0336
	P-value	0.3143	0.0015	0.0001	0.0375	0.0490
$\frac{1}{16}$ $mi.$	Mean	2.2450 **	1.7617 **	8.4709 **	0.5321 *	2.8069
	St. Dev	(10.2381)	(11.1467)	(15.0175)	(3.1544)	(9.8506)
	T-value	2.5801	2.6381	3.9959	2.2454	1.4930
	P-value	0.0105	0.0086	0.0002	0.0306	0.1437
	2015 Assault Density per sq. mile			0.4519		
	2015 Assault Standard Deviation			(2.2909)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Bus Stops and religious centers in 2016, across all distances demonstrated a high statistical significance when compared with overall assault density rate of 7.5641. Parks proved statistically significant across all regions, they only demonstrated statistically high significance at one-fourth and one-eighth mile distances. Emergency stations proved to be statistically significant across all distances and schools did not show any indication of significance with assault. In 2016, religious centers contained the highest mean value at one-fourth mile and schools demonstrated the lowest at one-sixteenth mile. Religious centers contained the highest mean values for assault within one-fourth mile buffer, while schools contained the lowest mean within one-sixteenth mile buffer. Standard deviations for all cells continued to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 7 2016 Assault Density Significance per Square Mile

Assault Density per Sq. mile 2016		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	10.4684	16.2935 **	120.1676 **	326.1742 **	36.5522 *
	St. Dev	(27.6499)	(53.1489)	(132.8851)	(729.8593)	(88.1066)
	T-value	1.5651	3.7382	6.5434	5.5733	2.0547
	P-value	0.1190	0.0002	0.0001	0.0001	0.0468
$\frac{1}{8}$ *mi.*	Mean	8.5228	18.3406 **	187.5607 **	20.5034 **	30.3113 *
	St. Dev	(22.7696)	(88.8478)	(279.6269)	(42.0981)	(68.0079)
	T-value	0.6245	2.7418	4.8598	3.9121	2.0888
	P-value	0.5329	0.0063	0.0001	0.0001	0.0435
$\frac{1}{16}$ *mi.*	Mean	9.8092	23.5787 *	139.6624 **	18.8533 **	21.2080 *
	St. Dev	(56.2528)	(175.391)	(257.0331)	(47.4296)	(37.9257)
	T-value	0.5879	2.0499	3.8459	3.0107	2.2467
	P-value	0.5572	0.0409	0.0003	0.0030	0.0306
	2016 Assault Density per sq. mile			7.5641		
	2016 Assault Standard Deviation			(28.4219)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

5.1.2 Bike Theft

The following section contains the significance testing results for bike theft in Seattle, when analyzed by its colocation within the predefined mile distances around the specified infrastructure points. In 2013, bike theft demonstrated statistical significance at bus stops, emergency stations and religious centers, with all three displaying high statistical significance at one-sixteenth mile distance, when compared with the overall bike theft density rate of 0.0191. Emergency stations displayed an additional area of high statistical significance at one-eighth mile. Bus stops and religious centers showed statistical significance at one-fourth mile, schools and parks displayed no statistical significance when analyzed against bike theft in 2013. The highest mean value occurred around religious centers at one-fourth mile. Bus stops, religious centers, and emergency stations all tied at one-sixteenth mile distance, with emergency stations having an additional low mean at one-eighth mile. Standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 8 2013 Bike Theft Density Significance per Square Mile

Bike Theft Density per Sq. mile 2013		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi*.	Mean	0.0239	0.0219	0.1440 *	1.9401 **	0.0194
	St. Dev	(0.1677)	(0.1439)	(0.3323)	(8.4321)	(0.1216)
	T-value	0.4306	0.4574	2.8632	2.9087	0.0192
	P-value	0.6672	0.6476	0.0059	0.0041	0.9848
$\frac{1}{8}$ *mi*.	Mean	0.0414	0.0237	0.1066	0.0187	0 **
	St. Dev	(0.4572)	(0.2680)	(0.5641)	(0.2387)	(0)
	T-value	0.7246	0.3953	1.1714	0.0182	0
	P-value	0.4695	0.6928	0.2464	0.9855	0
$\frac{1}{16}$ *mi*.	Mean	0.0560	0.0241	0 **	0 **	0 **
	St. Dev	(0.8257)	(0.5418)	(0)	(0)	(0)
	T-value	0.6592	0.2086	0	0	0
	P-value	0.5104	0.8349	0	0	0
	2013 Bike Theft Density per sq. mile			0.0191		
	2013 Bike Theft Standard Deviation			(0.1302)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when $P < 0.05$. (**) denotes blocks of statistically high significance when $P < 0.01$.

In 2014, all categories of infrastructure at one-eighth mile displayed some statistical significance with bus stop, religious centers, and emergency stations displaying high statistical significance when compared with overall bike theft density of 0.0339. The one-fourth mile distance indicated that parks, bus stops, and religious centers all demonstrated a statistical significance with bus stops and religious centers revealing a statistical high significance, while parks were only significant with bike theft. Emergency stations demonstrated a statistical high significance at one-eighth and one-sixteenth mile distance. The highest mean value occurred around religious centers at one-fourth mile. Emergency stations possessed the lowest mean at one-sixteenth and one-eighth mile buffered distances. Standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at the one-fourth mile.

Table 9 2014 Bike Theft Density Significance per Square Mile

Bike Theft Density per Sq. mile 2014		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0.0410	0.0777 *	1.0213 **	1.9401 **	0.0389
	St. Dev	(0.2001)	(0.4425)	(1.4406)	(8.4321)	(0.1697)
	T-value	0.5324	2.2527	5.2200	2.8863	0.1857
	P-value	0.5950	0.0247	0.0001	0.0044	0.8536
$\frac{1}{8}$ *mi.*	Mean	0.1243 *	0.1189 *	0.9596 **	0.3939 **	0 **
	St. Dev	(0.6695)	(0.9440)	(2.6416)	(1.7644)	(0)
	T-value	2.0030	2.0363	2.6458	2.5971	0
	P-value	0.0464	0.0422	0.0106	0.0103	0
$\frac{1}{16}$ *mi.*	Mean	0.1121	0.1448	1.0860	0.5321	0 **
	St. Dev	(1.1650)	(1.8731)	(6.6729)	(4.3881)	(0)
	T-value	0.9889	1.3292	1.1799	1.4363	0
	P-value	0.3238	0.1844	0.2431	0.1529	0
	2014 Bike Theft Density per sq. mile			0.0339		
	2014 Bike Theft Standard Deviation			(0.2741)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Religious centers and bus stops in 2015, displayed statistical significance when compared with the overall bike theft density of 0.1388. Religious centers demonstrated a statistically high significance at one-fourth mile buffer, while for bus stops the statistically high significance occurred at one-sixteenth mile. Emergency stations revealed significance at one-fourth mile. Schools only demonstrated a statistical significance within one-eighth mile buffer. Parks exhibited no statistical significance, when compared to the density of bike theft throughout 2015. The highest mean value occurred around religious centers at one-fourth mile and the lowest mean value was bus stops at one-sixteenth mile. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 10 2015 Bike Theft Density Significance per Square Mile

Bike Theft Density per Sq. mile 2015		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ $mi.$	Mean	0.2668	0.1993	0.1964	4.9996 **	0.4478 *
	St. Dev	(1.3367)	(0.8989)	(0.3354)	(18.1185)	(0.8119)
	T-value	1.4272	1.5343	1.3080	3.4252	2.3773
	P-value	0.1549	0.1256	0.1961	0.0008	0.0226
$\frac{1}{8}$ $mi.$	Mean	0.9254 *	0.1962	0.1066	0.3001	0.6233
	St. Dev	(5.5429)	(1.4671)	(0.5641)	(1.6317)	(1.9939)
	T-value	2.1051	0.8852	0.4305	1.2585	1.5177
	P-value	0.0364	0.3765	0.6685	0.2100	0.1374
$\frac{1}{16}$ $mi.$	Mean	1.1210	0.1689	0 **	0.0760	1.5594
	St. Dev	(13.0374)	(2.9156)	(0)	(0.9616)	(6.9367)
	T-value	1.1098	0.2320	0	0.8258	1.2789
	P-value	0.2683	0.8166	0	0.4102	0.2087
	2015 Bike Theft Density per sq. mile			0.1388		
	2015 Bike Theft Standard Deviation			(0.8956)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

In 2016, bus stops and religious centers proved to be statistically highly significant across all distances, when compared with the overall bike theft density of 1.5727. Schools showed a borderline statistical significance across all distances. Parks demonstrated a statistical significance at one-fourth mile and one-eighth mile distance. Emergency stations demonstrated no significance, when compared to the overall bike theft density. The highest mean value occurred around religious centers at one-fourth mile and the lowest mean value occurred at schools in one-sixteenth mile distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 11 2016 Bike Theft Density Significance per Square Mile

Bike Theft Density per Sq. mile 2016		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	2.1689 *	2.5350 **	14.7574 **	54.6235 **	2.7068
	St. Dev	(4.3701)	(5.4063)	(14.2249)	(89.0588)	(3.7965)
	T-value	2.0329	4.0511	7.0588	7.6052	1.8656
	P-value	0.0433	0.0001	0.0001	0.0001	0.0698
$\frac{1}{8}$ *mi.*	Mean	2.8176 *	2.6999 **	14.7148 **	3.3015 **	3.4285
	St. Dev	(8.4987)	(7.0318)	(16.4233)	(7.9894)	(7.0473)
	T-value	2.1732	3.6238	6.0414	2.7542	1.6445
	P-value	0.0308	0.0003	0.0001	0.0066	0.1083
$\frac{1}{16}$ *mi.*	Mean	0.8962 *	2.3892	14.9871 **	5.4735 **	3.1188
	St. Dev	(4.5542)	(11.7770)	(37.1109)	(17.7238)	(14.1513)
	T-value	2.1879	1.5505	2.705	2.7839	0.6823
	P-value	0.0297	0.1216	0.0091	0.0060	0.4992
	2016 Bike Theft Density per sq. mile			1.5727		
	2016 Bike Theft Standard Deviation			(4.3205)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

5.1.3 Burglary

The following section contains significance testing results for burglary in Seattle when analyzed by its colocation with the predefined distances around the infrastructure points. In 2013, burglary demonstrated a statistically high significance at religious centers and schools when compared against the overall burglary density rate of 0.1417. Religious centers continue to display statistically high significance across all distances. Schools displayed statistically high significance at one-eighth and one-sixteenth mile. No other infrastructure demonstrated statistical significance in 2013, when compared to the overall burglary density rate. The highest mean value occurred around religious centers at one-fourth mile. Religious centers and schools tied at one-sixteenth mile with the lowest mean. Standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 12 2013 Burglary Density Significance per Square Mile

Burglary Density per Sq. mile 2013		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi*.	Mean	0.1573	0.1686	0.2880	2.9102 **	0.3310
	St. Dev	(0.5560)	(0.5780)	(0.6646)	(10.0986)	(0.9510)
	T-value	0.4199	1.0596	1.6772	3.5001	1.2434
	P-value	0.6750	0.2898	0.0990	0.0006	0.2214
$\frac{1}{8}$ *mi*.	Mean	0.0552 **	0.1665	0.1066	0.0375 **	0.4675
	St. Dev	(0.4999)	(1.1919)	(0.5641)	(0.3366)	(1.7827)
	T-value	2.5647	0.4706	0.4694	3.9394	1.1414
	P-value	0.0110	0.6381	0.6406	0.0001	0.2608
$\frac{1}{16}$ *mi*.	Mean	0 **	0.4102	0.2172	0 **	0.9356
	St. Dev	(0)	(4.2158)	(1.6254)	(0)	(4.3091)
	T-value	0	1.4302	0.3476	0	1.1506
	P-value	0	0.1533	0.7295	0	0.2571
	2013 Burglary Theft Density per sq. mile			0.1417		
	2013 Burglary Standard Deviation			(0.6139)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Burglary in 2014, demonstrated a high significance at religious centers and bus stops. Both features only displayed a statistically high significance when compared at one-eighth mile distance. No other infrastructure proved significant when compared against the overall burglary density rate of 0.5508. The highest mean value occurred around religious centers at one-fourth mile, while parks demonstrated the lowest mean at one-fourth mile. The standard deviations for all cells continue to be considerably large compared to the mean values, indicating a large amount of variation within the distance-bands, with bus stops having the largest at one-fourth mile.

Table 13 2014 Burglary Density Significance per Square Mile

Burglary Density per Sq. mile 2014		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0.6602	0.5791	1.3225 **	12.4619 **	0.6221
	St. Dev	(1.4058)	(1.2262)	(1.9945)	(19.5827)	(1.0906)
	T-value	1.1602	0.5260	2.9468	7.7656	1.2434
	P-value	0.2472	0.5991	0.0046	0.0001	0.2214
$\frac{1}{8}$ *mi.*	Mean	0.5939	0.6244	1.0662	0.6190	1.0908
	St. Dev	(2.0390)	(2.3899)	(3.5630)	(2.1189)	(2.2577)
	T-value	0.3140	0.6965	1.0923	0.4099	1.1414
	P-value	0.7538	0.4864	0.2794	0.6824	0.2608
$\frac{1}{16}$ *mi.*	Mean	0.6726	0.5792	8.6997	0.9122	1.8712
	St. Dev	(4.7784)	(5.1695)	(53.4548)	(4.2157)	(6.5671)
	T-value	1.5852	0.1234	1.1408	1.0845	1.1506
	P-value	0.1144	0.9019	0.2589	0.2798	0.2571
	2014 Burglary Theft Density per sq. mile			0.5508		
	2014 Burglary Standard Deviation			(1.5889)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

In 2015, bus stops, religious centers, and emergency stations showed varying degrees of statistical significance when compared against the overall burglary density rate of 0.6852. Bus stops proved to be statistically highly significant around one-fourth and one-eighth mile distance, with one-sixteenth mile showing a statistical significance. Religious centers demonstrated statistically high significance at one-fourth mile and only statistical significance at one-eighth mile distance. Finally, emergency stations displayed a statistically high significance at one-sixteenth mile distance. No other infrastructure demonstrated significance, when tested against the overall burglary density in 2015. The highest mean value occurred around religious centers at one-fourth mile, while emergency stations demonstrated the lowest mean at one-sixteenth mile distance. The standard deviations for all cells continue to be quite large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 14 2015 Burglary Density Significance per Square Mile

Burglary Density per Sq. mile 2015		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0.7972	0.7345	2.8153 **	18.6555 **	0.6231
	St. Dev	(1.3009)	(1.4841)	(3.6214)	(29.6800)	(1.1408)
	T-value	1.2817	0.7568	4.4795	7.7301	0.3396
	P-value	0.2013	0.4495	0.0001	0.0001	0.7360
$\frac{1}{8}$ *mi.*	Mean	0.8011	0.8325	3.6787 **	1.1255*	0.7792
	St. Dev	(2.5209)	(3.7525)	(7.9315)	(2.7493)	(1.5143)
	T-value	0.6823	0.8878	2.8494	2.0385	0.3877
	P-value	0.4957	0.3750	0.0061	0.0431	0.7004
$\frac{1}{16}$ *mi.*	Mean	0.8968	1.0860	5.4301 *	0.6267	0 **
	St. Dev	(6.8657)	(7.1741)	(15.1956)	(2.3637)	(0)
	T-value	0.4541	1.2443	2.3367	0.3126	0
	P-value	0.6202	0.2103	0.0231	0.7550	0
	2015 Burglary Theft Density per sq. mile			0.6852		
	2015 Burglary Standard Deviation			(1.6278)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

All infrastructure in 2016, demonstrated varying trends of statistical significance except for schools at one-eighth and one-sixteenth mile when compared against the overall burglary density rate of 17.5975. Parks and religious centers showed statistically significant results across all distances. Bus stops and emergency stations exhibited, statistically high significances at one-fourth and one-eighth mile. Both infrastructures also demonstrated a statistical significance at one-sixteenth mile distance band. Schools only demonstrated a statistical significance at one-fourth mile distance. The highest mean value occurred around religious centers at one-fourth mile, while schools demonstrated the lowest mean at one-eighth mile buffered distance. The standard deviations for all cells continue to be quite large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 15 2016 Burglary Density Significance per Square Mile

Burglary Density per Sq. mile 2016		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ $mi.$	Mean	20.9574*	25.8163 **	104.6769 **	481.1648 **	35.5133**
	St. Dev	(23.0783)	(39.0102)	(127.5186)	(514.7506)	(38.2472)
	T-value	2.1692	4.7951	5.2006	11.4977	3.0886
	P-value	0.0311	0.0001	0.0001	0.0001	0.0037
$\frac{1}{8}$ $mi.$	Mean	20.5542	25.9154 **	122.4103 **	37.16125 **	40.1294 **
	St. Dev	(30.0317)	(60.8879)	(207.6041)	(55.0866)	(43.5397)
	T-value	1.4603	4.4174	3.8117	4.5203	3.2318
	P-value	0.1456	0.0001	0.0003	0.0001	0.0025
$\frac{1}{16}$ $mi.$	Mean	22.0287	26.7161 **	109.6054 *	37.4786 **	48.9656 *
	St. Dev	(63.3289)	(69.1825)	(297.3364)	(86.3213)	(85.5313)
	T-value	1.0307	2.9589	2.3232	2.9133	2.2903
	P-value	0.3038	0.0032	0.0239	0.0041	0.0276
	2016 Burglary Theft Density per sq. mile			17.5975		
	2016 Burglary Standard Deviation			(27.6189)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

5.1.4 Car Prowling

The following section contains the significance testing results for car prowling in Seattle, when analyzed by its colocation with the predefined distances around infrastructure points. In 2013, parks, bus stops, religious centers and emergency stations showed varying degrees of statistical significance, when compared against the overall car prowling density rate of 0.6852. Parks proved to have statistically highly significant at one-sixteenth mile, while bus stops were statistically highly significant at one-fourth and one-sixteenth mile distance. Religious centers only showed a statistically high significance at one-fourth mile distance. Bus stops proved to be statistically highly significant around one-fourth and one-eighth mile distance with one-sixteenth mile proving significant. Finally, emergency stations showed a statistically high significance at one-eighth and one-sixteenth mile distances. Schools demonstrated no significance, when tested against the overall car prowling density in 2013. The highest mean value occurred around religious centers at one-fourth mile, emergency stations, parks, and bus stops all tied for demonstrating the lowest mean value at one-sixteenth mile. Emergency stations had an additional low mean at one-eighth mile distance. The standard deviations for all cells continue to be quite large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 16 2013 Car Prowling Density Significance per Square Mile

Car Prowling Density per Sq. mile 2013		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0.1060	0.1554	0.4583 **	1.1193**	0.13631
	St. Dev	(0.7450)	(0.9124)	(0.9322)	(4.4434)	(0.6251)
	T-value	0.4390	0.6055	3.057	2.9745	0.5217
	P-value	0.6611	0.5451	0.0034	0.0034	0.6049
$\frac{1}{8}$ *mi.*	Mean	0.3177	0.2259	0.4265	0.2063	0 **
	St. Dev	(2.9228)	(2.7019)	(1.8555)	(0.8383)	(0)
	T-value	1.1854	1.1871	1.3933	1.8559	0
	P-value	0.2371	0.2358	0.1690	0.0653	0
$\frac{1}{16}$ *mi.*	Mean	0.9528	0 **	0 **	0.2280	0 **
	St. Dev	(11.6358)	(0)	(0)	(1.6550)	(0)
	T-value	1.0999	0	0	1.1003	0
	P-value	0.2726	0	0	0.2729	0
	2013 Car Prowling Density per sq. mile			0.0841		
	2013 Car Prowling Standard Deviation			(0.6584)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Car Prowling in 2014, demonstrated statistical significance at parks, religious centers, bus stops, and emergency stations when compared against the overall car prowling density rate of 0.1582. Parks displayed a statistically high significance at one-fourth and one-eighth mile distance. Bus stops possessed a statistically high significance at one-fourth and one-eighth mile distance and showed a significance at one-sixteenth mile. Religious centers showed statistically high significance at one-fourth mile and at one-eighth mile distances. Emergency stations proved to be statistically highly significant at one-eighth mile distance. The highest mean value occurred around religious centers at one-fourth mile, while schools demonstrated the lowest mean at one-sixteenth mile distance. The standard deviations for all cells continue to be reasonably large in comparison to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 17 2014 Car Prowling Density Significance per Square Mile

Car Prowling Density per Sq. mile 2014		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ $mi.$	Mean	0.1881	0.2829 **	1.8070 **	6.4921**	0.5257
	St. Dev	(0.5487)	(0.8229)	(2.3967)	(13.6682)	(1.2821)
	T-value	0.8134	3.3936	5.2393	5.9164	1.7904
	P-value	0.4168	0.0007	0.0001	0.0001	0.0814
$\frac{1}{8}$ $mi.$	Mean	0.2486	0.4341 **	1.3861 **	0.3751*	1.2467**
	St. Dev	(1.2411)	(1.8380)	(2.9323)	(1.3868)	(2.7640)
	T-value	1.0808	3.4505	3.1617	1.9913	2.4594
	P-value	0.2810	0.0006	0.0025	0.0481	0.0102
$\frac{1}{16}$ $mi.$	Mean	0.1681	0.3378	2.1720 *	0.7602	1.2475
	St. Dev	(1.8429)	(2.7446)	(7.3740)	(4.6637)	(4.6650)
	T-value	0.0796	1.4696	2.0437	1.6328	1.4583
	P-value	0.9366	0.1423	0.0458	0.1045	0.1530
	2014 Car Prowling Density per sq. mile			0.1582		
	2014 Car Prowling Standard Deviation			(0.6551)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

In 2015, bus stops, parks, and religious centers, showed varying degrees of statistical significance when compared against the overall car prowling density rate of 0.2894. Bus stops proved to be statistically highly significant around one-fourth and one-eighth mile distance with one-sixteenth mile proving statistically significant. Religious centers showed statistically high significance at one-fourth mile distance. Schools and emergency stations demonstrated no significance when tested against the overall car prowling density in 2015. The highest mean value occurred around religious centers at one-fourth mile, while schools demonstrated the lowest mean at one-sixteenth mile distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 18 2015 Car Prowling Density Significance per Square Mile

Car Prowling Density per Sq. mile 2015		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0.2805	0.5366 **	3.8890 **	10.2232 **	1.2463
	St. Dev	(1.0977)	(1.9843)	(5.3666)	(33.6499)	(3.6733)
	T-value	0.1204	2.8355	5.1082	4.3507	1.6268
	P-value	0.9043	0.0048	0.0001	0.0001	0.1120
$\frac{1}{8}$ *mi.*	Mean	0.2210	0.5173	4.8516 **	0.6753	1.0129
	St. Dev	(0.9813)	(2.6238)	(11.2372)	(4.5315)	(2.8176)
	T-value	1.0336	1.9642	3.0652	1.0839	1.6037
	P-value	0.3024	0.0600	0.0033	0.2800	0.1171
$\frac{1}{16}$ *mi.*	Mean	0.0560 **	1.1342	3.6924 *	0.6081	0.9356
	St. Dev	(0.8257)	(8.6539)	(12.0344)	(4.2705)	(5.8431)
	T-value	4.1630	1.6502	2.1161	0.3684	0.6907
	P-value	0.0001	0.0995	0.0389	0.7131	0.4940
	2015 Car Prowling Density per sq. mile			0.2894		
	2015 Car Prowling Standard Deviation			(1.4252)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Car Prowling in 2016, demonstrated statistical significance at parks, religious centers, bus stops, and emergency stations when compared against the overall car prowling density rate of 15.8017. Parks displayed a statistically high significance at one-fourth and one-eighth mile distances, while only demonstrating a significance at one-sixteenth mile distance. Bus stops displayed statistical high significance across all distance. Religious centers showed statistically high significance at one-fourth and one-eighth mile distance and only demonstrated significance at one-sixteenth mile.

Emergency stations only proved to be statistically significant at one-fourth mile buffered distance. The highest mean value occurred around religious centers at one-fourth mile, and schools demonstrated the lowest mean at one-eighth mile buffered distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 19 2016 Car Prowling Density Significance per Square Mile

Car Prowling Density per Sq. mile 2016		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	19.1374	24.9409 **	140.5426 **	458.6289 **	28.7043 *
	St. Dev	(27.2953)	(54.0372)	(175.2127)	(763.2336)	(39.6091
	T-value	2.0816	4.6917	5.4220	7.4075	2.0343
	P-value	0.0386	0.0001	0.0001	0.0001	0.0489
$\frac{1}{8}$ *mi.*	Mean	18.3993	24.8704 **	157.0648 **	30.3893 **	25.9478
	St. Dev	(36.5084)	(58.1055)	(224.0987)	(71.2008)	(34.3309)
	T-value	1.0554	3.5281	4.7591	2.6077	1.8456
	P-value	0.2924	0.0005	0.0001	0.0100	0.0727
$\frac{1}{16}$ *mi.*	Mean	21.0197	23.8442 *	157.9075 **	38.3148 *	25.5744
	St. Dev	(83.9081)	(86.5865)	(263.5593)	(140.0413)	(42.5761)
	T-value	0.9161	2.0852	4.0349	2.0335	1.4334
	P-value	0.3606	0.0376	0.0002	0.0437	0.1599
	2016 Car Prowling Density per sq. mile			15.8017		
	2016 Car Prowling Standard Deviation			(33.4777)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

5.1.5 Homicide

The following section contains the significance testing results for homicides in Seattle, when analyzed by its colocation with the predefined distances around the infrastructure points. In 2013, all infrastructures showed varying degrees of statistical significance when compared against the overall homicide density rate of 0.0147. Schools displayed a statistically high significance at one-sixteenth mile distance only. Parks demonstrated a statistical significance at one-fourth mile and one-sixteenth mile distances. Bus stops displayed statistically high significance across all distances. Religious Centers only showed statistical significance at one-fourth mile distance. Emergency stations indicated a statistically high significance at one-sixteenth mile buffer. The highest mean value occurred around religious centers at one-fourth mile, while emergency stations, parks, schools, and bus stops all tied, demonstrating the lowest mean value at one-sixteenth mile with bus stops having an additional low means at one-eighth and one-fourth mile distances. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 20 2013 Homicide Density Significance per Square Mile

Homicide Density per Sq. mile 2013		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0.0307	0.0058 **	0 **	0.7462 **	0.0389
	St. Dev	(0.1501)	(0.0665)	(0)	(2.9278)	(0.1697
	T-value	1.5969	3.0218	0	3.1899	0.8923
	P-value	0.1117	0.0026	0	0.0017	0.3779
$\frac{1}{8}$ *mi.*	Mean	0.0276	0.0178	0 **	0.0562	0.0779
	St. Dev	(0.2890)	(0.2323)	(0)	(0.4109)	(0.4866)
	T-value	0.6632	0.3055	0	1.2876	0.8113
	P-value	0.5079	0.7601	0	0.1997	0.4222
$\frac{1}{16}$ *mi.*	Mean	0 **	0 **	0 **	0.1520	0 **
	St. Dev	(0)	(0)	(0)	(1.3556)	(0)
	T-value	0	0	0	1.2815	0
	P-value	0	0	0	0.2019	0
	2013 Homicide Density per sq. mile			0.0147		
	2013 Homicide Standard Deviation			(0.1113)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Homicides in 2014, demonstrated statistical significance at bus stops, schools, religious centers, and emergency stations when compared against the overall homicide density rate of 0.0295. Schools had two buffered distances that displayed statistically high significance; the first distance was one-eighth mile distance and second distance was one-sixteenth mile. Parks displayed no detectable statistical significance when analyzed against the homicide density of 2014. Bus stops indicated a statistically high significance at one-fourth mile distance. Religious Centers showed a significance at one-sixteenth mile. Emergency stations demonstrated a statistically high significance at one-eighth and one-sixteenth mile distances. The highest mean value occurred around religious centers at one-fourth mile, while schools, religious centers, and emergency stations demonstrated the lowest mean at one-sixteenth mile buffered distance. Schools and emergency stations respectively had an additional low mean at one-eighth mile. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 21 2014 Homicide Density Significance per Square Mile

Homicide Density per Sq. mile 2014		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi*.	Mean	0.0684	0.0586	0.4321 **	0.5223	0.1168
	St. Dev	(0.7192)	(0.5311)	(0.9010)	(3.4055)	(0.5091)
	T-value	0.8063	1.2488	2.7365	1.5161	1.0713
	P-value	0.4299	0.2123	0.0083	0.1315	0.2908
$\frac{1}{8}$ *mi*.	Mean	0 **	0.1189	0.4798	0.0187	0 **
	St. Dev	(0)	(1.5177)	(2.0538)	(0.2387)	(0)
	T-value	0	1.3321	1.6554	0.5726	0
	P-value	0	0.1834	0.1034	0.5677	0)
$\frac{1}{16}$ *mi*.	Mean	0 **	0.3137	1.3032	0 **	0 **
	St. Dev	(0)	(5.6534)	(6.8330)	(0)	(0)
	T-value	0	1.1287	1.3949	0	0
	P-value	0	0.2569	0.1688	0	0
	2014 Homicide Density per sq. mile			0.0295		
	2014 Homicide Standard Deviation			(0.6551)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

In 2015, all infrastructures showed varying degrees of statistical significance when compared against the overall homicide density rate of 0.0147. Schools displayed a statistically high significance across all distances. Parks demonstrated a statistically high significance at one-fourth mile and one-sixteenth mile buffer. Bus stops displayed a statistical significance at one-fourth mile, before transitioning into being statistically high significance at one-sixteenth and one-eighth mile. Religious Centers only showed a statistically high significance at one-eighth and one-sixteenth mile distances. Emergency stations indicated a statistically high significance across all distances. The highest mean value occurred around bus stops at one-fourth mile. Emergency stations, parks, schools, religious centers, and bus stops all tied with the lowest mean value at one-sixteenth. Schools, bus stops, religious centers and emergency stations had an additional low means at one-eighth mile buffered distance. Schools and emergency stations tied for the lowest mean value at one-fourth mile distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having largest at one-fourth mile.

Table 22 2015 Homicide Density Significance per Square Mile

Homicide Density per Sq. mile 2015		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0 **	0.0351 *	1.7376 *	0.2238	0 **
	St. Dev	(0)	(0.2187)	(6.3218)	(2.1250)	(0)
	T-value	0	2.1317	2.0395	1.2566	0
	P-value	0	0.0335	0.0462	0.2107	0
$\frac{1}{8}$ *mi.*	Mean	0 **	0.0237	0 **	0 **	0 **
	St. Dev	(0)	(0.3798)	(0)	(0)	(0)
	T-value	0	0.5408	0	0	0
	P-value	0	0.5889	0	0	0
$\frac{1}{16}$ *mi.*	Mean	0 **	0 **	0 **	0 **	0 **
	St. Dev	(0)	(0)	(0)	(0)	(0)
	T-value	0	0	0	0	0
	P-value	0	0	0	0	0
	2015 Homicide Density per sq. mile			0.0147		
	2015 Homicide Standard Deviation			(0.1846)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Homicide in 2016, demonstrated statistical significance at bus stops, schools, religious centers, and emergency stations when compared against the overall car prowling density rate of 0.1964. Schools had two buffered distances that displayed a statistically high significance; the first was one-eighth mile and the second was one-sixteenth mile distance. Parks displayed no detectable statistical significance when analyzed against the homicide density of 2016. Bus stops were statistically highly significant at one-fourth mile distance. Religious Centers showed statistically high significance at one-sixteenth and one-eighth mile distances. Emergency stations demonstrated statistically high significance at one-sixteenth mile. The highest mean value occurred around religious centers at one-fourth mile. Schools, religious centers, and emergency stations demonstrated the lowest mean at one-sixteenth mile buffered distance. Religious centers had an additional low mean at one-eighth mile. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 23 2016 Homicide Density Significance per Square Mile

Homicide Density per Sq. mile 2016		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ $mi.$	Mean	0.3797	0.3724	2.6188 **	5.8205	1.7721
	St. Dev	(2.7069)	(2.3927)	(6.1932)	(36.9216)	(6.0616)
	T-value	1.7554	1.6742	2.9789	1.9448	1.6234
	P-value	0.0806	0.0947	0.0042	0.0636	0.1128
$\frac{1}{8}$ $mi.$	Mean	0.0276 **	0.5649	2.9856	0 **	2.8051
	St. Dev	(0.4097)	(4.5660)	(11.3196)	(0)	(12.919)
	T-value	6.1091	1.8247	1.8603	0	1.2611
	P-value	0.0001	0.0686	0.0681	0	0.2150
$\frac{1}{16}$ $mi.$	Mean	0 **	0.3861	2.6064	0 **	0 **
	St. Dev	(0)	(6.8492)	(19.5049)	(0)	(0)
	T-value	0	0.6219	0.9246	0	0
	P-value	0	0.5343	0.3592	0	0
	2016 Homicide Density per sq. mile			0.1964		
	2016 Homicide Standard Deviation			(2.1689)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

5.1.6 Narcotics

The following section contains the significance testing results for narcotics in Seattle, when analyzed by its colocation with the predefined distances around infrastructure points. Narcotics in 2013, demonstrated varying degrees of statistical significance at schools, parks, bus stops, and religious centers when compared against the overall narcotics density rate of 0.0295. Schools had two buffered distances that displayed a statistically high significance; the first was one-eighth mile and the second was one-sixteenth mile distance. Parks displayed statistically high significance at one-fourth mile buffer distance and only demonstrated statistically significant results at one-eighth mile buffer. Bus stops showed statistically high significance across all distances. Religious centers generated a statistically high significance at one-fourth mile distance. Emergency stations displayed no detectable statistical significance when analyzed against the narcotics density of 2013. The highest mean value occurred around religious centers at one-fourth mile. Schools demonstrated the lowest mean at one-sixteenth mile buffered distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 24 2013 Narcotics Density Significance per Square Mile

Narcotics Density per Sq. mile 2013		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ $mi.$	Mean	0.1710	0.4955 **	4.4521 **	8.3577 **	1.4021
	St. Dev	(0.7416)	(2.1937)	(6.9190)	(32.7307)	(3.8194)
	T-value	0.8648	2.9202	4.6647	3.1765	1.9425
	P-value	0.3881	0.0037	0.0001	0.0018	0.0605
$\frac{1}{8}$ $mi.$	Mean	0.0414 **	0.5530 *	6.7176 **	1.1067	1.4021
	St. Dev	(0.6146)	(3.8816)	(13.5873)	(6.0849)	(3.8194)
	T-value	4.1665	1.9741	3.6137	1.8672	1.5493
	P-value	0.0001	0.0489	0.0006	0.0637	0.1296
$\frac{1}{16}$ $mi.$	Mean	0 **	0.6998	3.4752 **	0.1520	0.3118
	St. Dev	(0)	(6.8026)	(10.0340)	(1.9232)	(1.9477)
	T-value	0	1.6032	2.4322	0.4082	0.3135
	P-value	0	0.1095	0.0183	0.6837	0.7556
	2013 Narcotics Density per sq. mile			0.2141		
	2013 Narcotics Standard Deviation			(1.4242)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

In 2014, all infrastructure showed varying degrees of statistical significance when compared against the overall narcotics density rate of 0.1801. Schools displayed statistical significance at one-fourth mile; parks also demonstrated a statistically high significance at one-fourth mile and indicated significance at one-sixteenth mile distances. Bus stops displayed a statistically high significance at one-fourth mile and one-eighth mile, in addition to indicating significance at one-sixteenth mile. Religious centers and emergency stations continued to show a statistically high significance at one-fourth mile buffer only. The highest mean value occurred around bus stops at one-sixteenth mile, while parks demonstrated the lowest mean value at one-fourth mile. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 25 2014 Narcotics Density Significance per Square Mile

Narcotics Density per Sq. mile 2014		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ $mi.$	Mean	2.0184 *	0.1160 **	3.3259 **	7.8353 **	1.9668 **
	St. Dev	(9.3271)	(0.5719)	(5.8411)	(25.1276)	(4.9303)
	T-value	2.9366	2.7419	4.1016	2.9770	2.2632
	P-value	0.0037	0.0063	0.0001	0.0034	0.0146
$\frac{1}{8}$ $mi.$	Mean	0.3177	0.5709 *	6.2378 **	0.4689	2.9610
	St. Dev	(1.7253)	(3.9323)	(15.8472)	(2.3114)	(10.6302)
	T-value	1.1829	2.2466	2.8860	1.5907	1.6337
	P-value	0.2381	0.0251	0.0055	0.1136	0.1106
$\frac{1}{16}$ $mi.$	Mean	0.2802	1.3032	12.3806 *	0.1520	1.2475
	St. Dev	(3.4007)	(13.1534)	(44.3433)	(1.9232)	(5.4359)
	T-value	0.4339	1.9169	2.0589	0.1845	1.2263
	P-value	0.6648	0.0658	0.0442	0.8538	0.2276
	2014 Narcotics Density per sq. mile			0.1801		
	2014 Narcotics Standard Deviation			(1.2598)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Narcotics in 2015, demonstrated varying degrees of statistical significance at schools, parks, bus stops, and religious centers when compared against the overall narcotics density rate of 0.2820. Schools displayed a statistical significance at one-eighth mile distance. Parks possessed a statistically high significance at one-fourth mile buffer distance and at one-eighth mile distance. Bus stops showed statistically high significance across two distances; the one-fourth and one-eighth mile, only demonstrating a statistical significance at one-sixteenth mile. Religious centers generated a high statistical significance at one-fourth mile buffer and indicated a statistical significance at one-eighth mile distance. Emergency stations displayed no detectable statistical significance when analyzed against the narcotics density of 2015. The highest mean value occurred around religious centers at one-fourth mile; schools demonstrated the lowest mean at one-sixteenth mile distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 26 2015 Narcotics Density Significance per Square Mile

Narcotics Density per Sq. mile 2015		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0.2600	0.7096 **	7.6733 **	11.3425 **	1.6357
	St. Dev	(0.9419)	(3.2490)	(10.9021)	(37.6513)	(5.1022)
	T-value	0.3480	2.9955	5.1633	3.7505	1.6570
	P-value	0.7282	0.0029	0.0001	0.0002	0.1058
$\frac{1}{8}$ *mi.*	Mean	0.1519 *	1.1120 **	11.8358 **	0.8066 *	2.1817
	St. Dev	(0.9286)	(7.1492)	(22.3439)	(3.1916)	(11.1755)
	T-value	2.0772	2.6247	3.9039	2.0922	1.0616
	P-value	0.0389	0.0089	0.0003	0.0380	0.2951
$\frac{1}{16}$ *mi.*	Mean	0.1121	1.3997	13.0322 *	0.4561	0.3118
	St. Dev	(1.6514)	(13.4968)	(43.0109)	(3.5801)	(1.9477)
	T-value	1.5155	1.8592	2.2184	0.6152	0.0958
	P-value	0.1311	0.0636	0.0307	0.5393	0.9242
	2015 Narcotics Density per sq. mile			0.2820		
	2015 Narcotics Standard Deviation			(1.9098)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Narcotics in 2016, demonstrated varying amounts of statistical significance at parks, bus stops, and religious centers when compared against the overall narcotics density rate of 3.8308. Schools and emergency stations displayed no statistical significance when compared against the overall narcotics density. Parks and bus stops both displayed a high statistical significance at one-fourth and one-eighth mile distances, indicating a statistical significance at one-sixteenth mile. Religious centers only displayed a statistically high significance at one-fourth mile distance. The highest mean value occurred around religious centers at one-fourth mile. Religious centers also demonstrated the lowest mean at one-sixteenth mile distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 27 2016 Narcotics Density Significance per Square Mile

Narcotics Density per Sq. mile 2016		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi*.	Mean	4.6560	9.7515 **	99.3212 **	107.083 **	18.5779
	St. Dev	(15.3625)	(42.8649)	(143.3753)	(394.0799)	(58.0260)
	T-value	0.8004	3.1437	5.0723	3.3451	1.5872
	P-value	0.4243	0.0018	0.0001	0.0001	0.1208
$\frac{1}{8}$ *mi*.	Mean	3.0251	13.6662 **	138.9911 **	3.8643	23.9997
	St. Dev	(11.1855)	(84.4198)	(279.8991)	(15.8687)	(92.2327)
	T-value	1.0684	2.6337	3.6457	0.0269	1.3656
	P-value	0.2865	0.0087	0.0006	0.9786	0.1801
$\frac{1}{16}$ *mi*.	Mean	2.9707	20.8998 *	142.9204 *	2.8127	24.32688
	St. Dev	(16.840)	(185.8608)	(456.4614)	(12.9577)	(20.4765)
	T-value	0.7523	2.0618	2.2803	0.9938	0.8292
	P-value	0.4527	0.0397	0.0265	0.3219	0.4122
	2016 Narcotics Density per sq. mile			3.8308		
	2016 Narcotics Standard Deviation			(2.1689)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

5.1.7 Robbery

The following section contains the significance testing results for robberies in Seattle when analyzed by its colocation with the predefined distances around previously specified infrastructures. Robbery in 2013, demonstrated strong statistical significance around bus stops, religious centers, and emergency stations when compared against the overall robbery density rate of 0.0324. Bus stops and religious centers displayed a statistically high significance at one-fourth and one-sixteenth mile distance. Emergency stations demonstrated high statistical significance at one-eighth mile and one-sixteenth mile distance. Schools and parks indicated no statistical significance in 2013, when compared with the overall robbery density. The highest mean value occurred around religious centers at one-fourth mile. Bus stops, religious centers, and emergency stations demonstrated the lowest mean at one-sixteenth mile distance. Emergency stations displayed an additional low mean at one-eighth mile. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 28 2013 Robbery Density Significance per Square Mile

Robbery Density per Sq. mile 2013		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi*.	Mean	0.0786	0.0351	0.4119**	2.6117 **	0.0194
	St. Dev	(0.4353)	(0.2606)	(1.1222)	(9.1405)	(0.1216)
	T-value	1.5841	0.2435	2.5976	3.6028	0.8923
	P-value	0.1146	0.8077	0.0119	0.0004	0.3779
$\frac{1}{8}$ *mi*.	Mean	0.0690	0.0297	0.4798	0.3001	0 **
	St. Dev	(0.8438)	(0.2994)	(3.6226)	(1.8922)	(0)
	T-value	0.6445	0.2012	0.9325	1.801	0
	P-value	0.5199	0.8406	0.3551	0.0736	0
$\frac{1}{16}$ *mi*.	Mean	0.0560	0.0241	0 **	0 **	0 **
	St. Dev	(0.8257)	(0.5418)	(0)	(0)	(0)
	T-value	0.4220	0.3425	0	0	0
	P-value	0.6735	0.7321	0	0	0
	2013 Robbery Density per sq. mile			0.0324		
	2013 Robbery Standard Deviation			(0.3040)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

In 2014, all infrastructure showed varying degrees of statistical significance when compared against the overall robbery density rate of 0.0738. Schools displayed statistically high significance at one-sixteenth mile. Parks demonstrated a statistical significance at one-fourth mile. Bus stops displayed a high statistical significance across all the tested distances. Religious centers only showed high statistical significance at one-fourth mile distance. Emergency stations only indicated a statistical significance at one-sixteenth mile distance. The highest mean value occurred around religious centers at one-fourth mile. Schools and emergency stations demonstrated the lowest mean value at one-sixteenth mile. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 29 2014 Robbery Density Significance per Square Mile

Robbery Density per Sq. mile 2014		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi*.	Mean	0.0957	0.1231 *	1.4534 **	2.6117 **	0.1752
	St. Dev	(0.4101)	(0.5572)	(1.6238)	(9.1405)	(0.6150)
	T-value	0.7987	2.0158	6.4707	3.5449	1.0302
	P-value	0.4253	0.0443	0.0001	0.0005	0.3094
$\frac{1}{8}$ *mi*.	Mean	0.1105	0.1427	2.2392 **	0.2063	0.1558
	St. Dev	(0.8641)	(1.0670)	(3.8750)	(1.1298)	(0.6790)
	T-value	0.6300	1.4603	4.2190	1.4932	0.7545
	P-value	0.5293	0.1448	0.0001	0.1373	0.4552
$\frac{1}{16}$ *mi*.	Mean	0 **	0.0965	2.8236 **	0.0760	0 **
	St. Dev	(0)	(1.3249)	(7.3315)	(0.9616)	(0)
	T-value	0	0.3852	2.8068	0.0292	0
	P-value	0	0.7002	0.0069	0.9767	0
	2014 Robbery Density per sq. mile			0.0738		
	2014 Robbery Standard Deviation			(0.5059)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Robbery in 2015, demonstrated statistical significance with schools, parks, bus stops, and religious centers when compared against the overall robbery density rate of 0.1388. Schools showed a statistically high significance to robberies at one-sixteenth mile distance. Parks and bus stops displayed statistically high significance at one-fourth and one-eighth mile distance. Religious centers indicated a high statistical significance at one-fourth mile distance band. Emergency stations indicated no statistical significance in 2015, when compared with the overall robbery density. The highest mean value occurred around religious centers at one-fourth mile. Schools provided the lowest mean at one-sixteenth mile. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 30 2015 Robbery Density Significance per Square Mile

Robbery Density per Sq. mile 2015		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi*.	Mean	0.1915	0.2756 **	1.6498 **	4.7012 **	0.5842
	St. Dev	(0.8361)	(1.0390)	(2.2989)	(13.8041)	(1.5235)
	T-value	0.9405	2.9973	5.0059	4.2197	1.8257
	P-value	0.3480	0.0029	0.0001	0.0001	0.0758
$\frac{1}{8}$ *mi*.	Mean	0.1243	0.3925 **	1.8126 **	0.4689	0.7792
	St. Dev	(0.8374)	(2.1339)	(3.5800)	(2.2099)	(3.9264)
	T-value	0.2565	2.6875	3.5300	1.9016	1.0186
	P-value	0.7978	0.0074	0.0008	0.0590	0.3148
$\frac{1}{16}$ *mi*.	Mean	0 **	0.6033	1.0860	0.5321	1.2475
	St. Dev	(0)	(4.7205)	(4.1986)	(5.8432)	(7.7908)
	T-value	0	1.5373	1.6882	0.8515	0.8887
	P-value	0	0.1248	0.0970	0.3958	0.3797
	2015 Robbery Density per sq. mile			0.1388		
	2015 Robbery Standard Deviation			(0.8019)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Robbery in 2016, demonstrated varying amounts of statistical significance around bus stops, religious centers, and emergency stations when compared against the overall robbery density rate of 4.6873. Parks and emergency stations both held statistically high significance at one-fourth and indicated significance at one-eighth mile. Bus stops and religious centers demonstrated a high statistical significance at one-fourth and one-eighth mile. Bus stops and religious centers also showed an additional statistical significance at one-sixteenth mile. The highest mean value occurred around religious centers at one-fourth mile, with schools demonstrating the lowest mean at one-eighth mile distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 31 2016 Robbery Density Significance per Square Mile

Robbery Density per Sq. mile 2016		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	6.0723	8.0199 **	27.5506 **	151.5422 **	15.7153**
	St. Dev	(13.7855)	(21.0810)	(24.0019)	(262.7096)	(22.6949)
	T-value	1.497	3.5980	5.5764	7.2885	3.0346
	P-value	0.1358	0.0004	0.0001	0.0001	0.0043
$\frac{1}{8}$ *mi.*	Mean	5.3457	8.1414 *	29.2697 **	11.1615 **	13.5583 *
	St. Dev	(26.4004)	(34.3903)	(35.5448)	(30.4342)	(26.7106)
	T-value	0.3699	2.2705	3.6428	2.7076	2.0741
	P-value	0.7118	0.0236	0.0006	0.0075	0.0449
$\frac{1}{16}$ *mi.*	Mean	8.1836	7.7469	21.0688 *	13.2277 *	21.2080
	St. Dev	(85.6884)	(45.7325)	(39.7363)	(48.4887)	(55.6502)
	T-value	0.6011	1.5020	2.3046	2.2279	1.8539
	P-value	0.5484	0.1337	0.0250	0.0273	0.0715
	2016 Robbery Density per sq. mile			4.6873		
	2016 Robbery Standard Deviation			(15.1715)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

5.1.8 Vehicle Theft

The following section contains the significance testing for vehicle theft in Seattle, when analyzed by its colocation with the predefined distances around the previously specified infrastructure points. In 2013, bus stops, religious centers, and emergency stations demonstrated varying degrees of statistical significance when compared to the overall vehicle theft density of 0.0620. Schools and parks displayed no statistical significance across any of the buffered distances. Bus stops showed a statistically high significance at one-sixteenth mile. Religious centers possessed statistically high significance at one-fourth mile. Emergency stations had statistically high significance at one-sixteenth mile and indicated a statistical significance at one-fourth mile. The highest mean value occurred around bus stops at one-fourth mile, with schools and emergency stations demonstrating the lowest means at one-sixteenth mile distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 32 2013 Vehicle Theft Density Significance per Square Mile

Vehicle Theft Density per Sq. mile 2013		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0.0650	0.0865	3.9096	0.9700 **	0.0194 *
	St. Dev	(0.3286)	(0.4750)	(20.4991)	(3.3053)	(0.1216)
	T-value	0.1360	1.1740	1.4046	3.5075	2.1838
	P-value	0.8919	0.2409	0.1658	0.0006	0.0352
$\frac{1}{8}$ *mi.*	Mean	0.1243	0.1189	0.4798	0.0750	0.077
	St. Dev	(0.9327)	(1.2852)	(3.6226)	(0.4730)	(0.4866)
	T-value	0.9910	1.0015	0.8708	0.3507	0.2043
	P-value	0.3228	0.3171	0.3876	0.7263	0.8392
$\frac{1}{16}$ *mi.*	Mean	0.0560	0.0965	0 **	0.0760	0 **
	St. Dev	(0.8257)	(1.0803)	(0)	(0.9616)	(0)
	T-value	0.1061	0.7176	0	0.1844	0
	P-value	0.9156	0.4733	0	0.8539	0
	2013 Vehicle Theft Density per sq. mile			0.0620		
	2013 Vehicle Theft Standard Deviation			(0.4792)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Vehicle theft in 2014, demonstrated statistical significance with bus stops, religious centers, and emergency stations when compared against the vehicle theft density of 0.2909. Schools and parks showed no statistical significance for vehicle theft in 2014. Bus stops displayed a statistically high significance at one-eighth mile distance. Religious centers indicated a high statistical significance at one-fourth mile distance. Emergency stations showed statistically high significance at one-sixteenth mile distance. The highest mean value occurred around religious centers at one-fourth mile, with emergency stations providing the lowest mean at one-sixteenth mile distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at the one-fourth mile.

Table 33 2014 Vehicle Theft Density Significance per Square Mile

Vehicle Theft Density per Sq. mile 2014		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0.3865	0.3342	0.6509	6.2682 **	0.4284
	St. Dev	(1.1371)	(0.9290)	(1.3541)	(14.8882)	(0.9977)
	T-value	1.2536	1.0629	1.9898	5.1258	0.8607
	P-value	0.2113	0.2883	0.0616	0.0001	0.3948
$\frac{1}{8}$ *mi.*	Mean	0.4420	0.2854	2.2925 **	0.4314	0.4675
	St. Dev	(1.8747)	(1.5312)	(5.1135)	(1.9418)	(1.6407)
	T-value	1.1957	0.0803	2.9553	0.9213	0.6723
	P-value	0.2331	0.9360	0.0046	0.3583	0.5055
$\frac{1}{16}$ *mi.*	Mean	0.4484	0.2654	3.6924	0.3040	0 **
	St. Dev	(3.4823)	(2.5873)	(13.7064)	(3.0351)	(0)
	T-value	0.6663	0.2206	1.8572	0.055	0
	P-value	0.5059	0.8255	0.0686	0.9562	0
	2014 Vehicle Theft Density per sq. mile			0.2909		
	2014 Vehicle Theft Standard Deviation			(1.0704)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

In 2015, parks, bus stops, religious centers, and emergency stations demonstrated varying degrees of statistical significance when compared to the overall vehicle theft density of 0.1978. Schools displayed no statistical significance across any of the distances tested. Parks showed a statistical significance at one-fourth and one-eighth mile. Bus stops possessed a statistically high significance at one-sixteenth and one-fourth mile distance. Religious centers possessed statistically high significance at one-fourth mile. Emergency stations had statistical significance at one-sixteenth mile. The highest mean value occurred around religious centers at one-fourth mile. Emergency stations and bus stops demonstrated the lowest means at one-sixteenth mile distance. The standard deviations for all cells continue to be reasonably large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 34 2015 Vehicle Theft Density Significance per Square Mile

Vehicle Theft Density per Sq. mile 2015		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	0.1744	0.2771 *	0.6154 **	5.6712 **	0.5257
	St. Dev	(0.6242)	(0.7762)	(0.9485)	(14.5737)	(1.2090)
	T-value	0.5568	2.3254	3.3531	4.7950	1.6941
	P-value	0.5782	0.0204	0.0014	0.0001	0.0984
$\frac{1}{8}$ *mi.*	Mean	0.2900	0.3984 *	0.7464	0.5064	0.7012
	St. Dev	(1.9153)	(2.1455)	(2.2449)	(2.3282)	(1.9044)
	T-value	0.7146	2.1140	1.8449	1.6875	1.6511
	P-value	0.4756	0.0350	0.0703	0.0934	0.1070
$\frac{1}{16}$ *mi.*	Mean	0.2242	0.1689	0 **	0.5321	0 **
	St. Dev	(2.6074)	(2.0936)	(0)	(4.9838)	(0)
	T-value	0.1492	0.3095	0	0.8486	0
	P-value	0.8815	0.7571	0	0.3974	0
	2015 Vehicle Theft Density per sq. mile			0.1978		
	2015 Vehicle Theft Standard Deviation			(0.8304)		

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

Vehicle theft in 2016, demonstrated statistical significance with schools, bus stops, religious centers, and emergency stations when compared against the vehicle theft density of 11.7878. Schools, parks, bus stops, religious centers, and emergency stations all demonstrated statistically high significance across the one-fourth mile distance. At one-eighth mile distance, schools, parks, bus stops, religious centers all continued to demonstrate a high statistical significance, while emergency stations only demonstrated a statistical significance. Only religious centers displayed statistically high significance at one-sixteenth mile distance. The highest mean value occurred around religious centers at one-fourth mile, while parks provided the lowest mean at one-sixteenth mile distance. The standard deviations for all cells continue to be quite large compared to the mean values, indicating a large amount of variation within the distance-bands, with religious centers having the largest at one-fourth mile.

Table 35 2016 Vehicle Theft Density Significance per Square Mile

Vehicle Theft Density per Sq. mile 2016		Schools	Parks	Bus Stops	Religious Centers	Emergency Stations
$\frac{1}{4}$ *mi.*	Mean	15.5248 **	15.1616 **	27.5506 **	318.2643 **	19.4932 **
	St. Dev	(15.6663)	(16.0001)	(24.0019)	(277.5839)	(16.3849)
	T-value	3.5541	4.7992	5.0015	14.0960	2.9369
	P-value	0.0005	0.0001	0.0001	0.0001	0.0056
$\frac{1}{8}$ *mi.*	Mean	16.6588 **	15.6585 **	29.2697 **	19.1715 **	20.4933 *
	St. Dev	(26.6189)	(25.2102)	(35.5448)	(24.4509)	(22.8874)
	T-value	2.7142	3.4708	3.7132	3.8436	2.3754
	P-value	0.0072	0.0006	0.0005	0.0002	0.0227
$\frac{1}{16}$ *mi.*	Mean	20.4031	12.7185	21.0688	21.1339 **	30.5645
	St. Dev	(65.4363)	(33.9730)	(39.7363)	(51.9373)	(58.7244)
	T-value	1.9395	0.6150	1.7478	3.8436	1.9968
	P-value	0.0637	0.5388	0.0861	0.0002	0.0630
	2016 Vehicle Theft Density per sq. mile		11.7878			
	2016 Vehicle Theft Standard Deviation		(15.3628)			

Note: Mean displayed on top and the standard deviation is encapsulated in parenthesis while (*) denotes blocks of statistical significance when P < 0.05. (**) denotes blocks of statistically high significance when P < 0.01.

<u>5.2 Spatial Data Mining of Crime Patterns Results</u>

The following tables display the results of the Apriori algorithm for association rule mining for the city of Seattle, census crime itemsets. Each table will display the association rules the Apriori algorithm created, with columns detailing the antecedents, consequents, support, confidence and the lift values. The Apriori algorithm used multiple minimum support values, during the result generation process, these values ranged from ninety percent to one percent for all itemsets. For the results, any association rules with a confidence value between ninety-three and nine-nine percent will be indicated with a single asterisk (*) in the confidence value column. This indicates these association rules consequents have a high probability of occurring, where the antecedent crimes are found. Rules with absolute certainty to occur have double asterisks (**) in the confidence column, these rules have a confidence value of one hundred percent. A one hundred percent confidence value indicates that this association rule at the minimum support value range will always occur. All association rules in this study used a confidence value of seventy percent as a baseline. This confidence value is stringent enough to remove rules from the generation process that have an impossible probability of occurrence. Enabling the results to focus on rules that would consistently occur to establish a pattern within the census blocks. The iterations of this setup in some cases generated up to six-hundred and one potential association rules, for census blocks and crime in Seattle. The results will only focus on detailing rules that have a confidence level above ninety-three percent, still providing the most prevalent rules for the census blocks and crime association.

5.2.1 2013 Association Rule Results

In 2013, the Apriori algorithm conducted twenty iterations and reviewed one-hundred and six-nine instances before generating the following strong association rules listed in 2013 Crime Association Rule table, when analyzing the eight different types of crime. The following are the association rules for crime in 2013, with a confidence value equal to or above ninety-three percent and the lift value is high enough to support the consequents, which are dependent on the antecedents:

1. In one to two percent of census blocks in Seattle, where homicide and vehicle theft occur, an assault has a one-hundred percent certainty of occurring in this area.
2. In one to two percent of census blocks in Seattle, where robbery, car prowling, and homicide occur, there is one-hundred percent certainty that assault will occur with that census block.
3. In one to two percent of census blocks in Seattle, where assault, robbery and car prowling occur, there is one-hundred percent certainty that homicides will occur within that census block.

More than previously listed rules are present in the association rule table, the lower confidence value does not support a high level of pattern reliability within the examined data. These results contained a confidence value between seventy and eighty percent, with lift values that indicate the consequents are dependent on the antecedents. This low confidence moves these association rules into the probable level of certainty, indicating there is a chance predicted crime still might not occur.

Table 36 2013 Crime Association Rules

Antecedents	Consequents	Support	Confidence	Lift
Robbery, Homicide	Assault	1-4%	70%	1.71
Homicide, Vehicle Theft	Assault	1-2%	100% (**)	1.78
Robbery, Car Prowling Homicide	Assault	1-2%	100% (**)	1.78
Assault, Robbery, Car Prowling	Homicide	1-2%	100% (**)	2.22
Homicide, Narcotics	Assault	1-2%	80%	1.48
Assault, Narcotics	Homicide	1-2%	80%	3.07
Robbery, Car Prowling	Assault	1-2%	75%	1.18
Robbery, Narcotics	Assault	1-2%	75%	1.18
Robbery, Car Prowling	Homicide	1-2%	75%	1.48
Assault, Car Prowling, Homicide	Robbery	1%	75%	2.49
Robbery, Car Prowling	Assault, Homicide	1%	75%	1.71
Note: (*) denotes Association Rules with a Confidence >= 75% but less than 93% and (**) denotes blocks of Confidence >= 93% but less than 100%. (**) is confidence values = 100%				

5.2.2 2014 Association Rule Results

The Apriori algorithm conducted twenty iterations and reviewed two-hundred and eighty-one instances, before generating the following results for strong association rules listed in the 2014 Crime Association Rule table, when analyzing the eight different types of crime. These are the association rules for crime in 2014, with a confidence value equal to or above ninety-three percent and the lift value is high enough to support the consequents, which are dependent on the antecedents:

1. In one to two percent of Seattle census blocks, where burglary and car prowling occur, there is a one-hundred percent certainty that assault will take place in that area.
2. In one percent of all Seattle census blocks, where homicide and narcotics crimes occur, there is a one-hundred percent certainty that an assault will take place in that census block.

3. In one percent of all Seattle census blocks, where burglary, robbery, and car prowling occur, there is a one-hundred percent certainty that assault will occur within that census block.
4. In one percent of all Seattle census blocks, where burglary, car prowling, and homicide occur, there is one-hundred percent certainty an assault will be reported.
5. In one percent of all Seattle census blocks, where assault, burglary, and homicide occur, there is a one-hundred percent certainty an incident of car prowling.
6. In one percent of all Seattle census blocks, where car prowling, homicide, and narcotics occur, there is a one-hundred percent certainty an incident of assault.
7. In one percent of all Seattle census blocks, where homicide, narcotics, and vehicle theft occur, there is a one-hundred percent certainty an incident of assault.

Previously listed rules are present in the 2014, association rules table; and the lower confidence value does not support a high level of pattern reliability within the examined data. These results contained confidence values between seventy and eighty-three percent, with lift values that indicate the consequents are dependent on the antecedents and the low confidence moves the results into a probable level of certainty, indicating there is a chance the consequent still might not occur. One association rule carried over from 2013 to 2014, listed homicide and narcotics as antecedents for assault.

This association rules confidence increased from eighty to one-hundred percent and maintained a dependent lift value for both years.

Table 37 2014 Crime Associations Rules

Antecedents	Consequents	Support	Confidence	Lift
Burglary, Car Prowling	Assault	1-2%	100% (**)	3.16
Homicide, Vehicle Theft	Car Prowling	1-2%	70%	3.28
Homicide, Narcotics	Assault	1%	100% (**)	3.16
Burglary, Robbery, Car Prowling	Assault	1%	100% (**)	3.16
Burglary, Car Prowling, Homicide	Assault	1%	100% (**)	3.16
Assault, Burglary, Homicide	Car Prowling	1%	100% (**)	4.68
Car Prowling, Homicide, Narcotics	Assault	1%	100% (**)	3.16
Homicide, Narcotics, Vehicle Theft	Assault	1%	100% (**)	3.16
Car Prowling, Narcotics	Assault	1%	83%	2.63
Narcotics, Vehicle Theft	Assault	1%	83%	2.63
Assault, Homicide, Vehicle Theft	Car Prowling	1%	80%	3.75
Burglary, Homicide	Assault	1%	75%	2.37
Burglary, Homicide	Car Prowling	1%	75%	3.51
Burglary, Homicide	Vehicle Theft	1%	75%	2.74
Burglary, Homicide	Assault, Car Prowling	1%	75%	9.16
Robbery, Car Prowling, Homicide	Assault	1%	75%	2.37
Assault, Robbery, Homicide	Car Prowling	1%	75%	3.51
Note: (*) denotes Association Rules with a Confidence >= 93% but less than or equal to 99% and (**) denotes blocks of Confidence = 100%				

5.2.2 2015 Association Rule Results

In 2015, the Apriori algorithm conducted twenty iterations and reviewed three-hundred and four instances before generating the following strong association rules listed in the 2015 Crime Association Rules table, when analyzing the eight different types of crime. These are the association rules for crime in 2015, with a confidence value equal to or above ninety-three percent and the lift, value is high enough to support the consequents, which are dependent on the antecedents:

1. In one to two percent of Seattle census blocks, where car prowling, homicide and vehicle theft occur, there is a one-hundred percent certainty that assault will take place in that area.
2. In one percent of Seattle census blocks, where car prowling, homicide and narcotics occur, there is a one hundred percent certainty that assault will occur.
3. In one percent of Seattle census blocks, where homicide, narcotics, and vehicle theft occur, there is a one hundred percent certainty that assault will take place.
4. In one percent of Seattle census blocks, where robbery, car prowling, homicide, and vehicle theft occur, there is a one hundred percent certainty that assault will occur.
5. In one percent of Seattle census blocks, where assault, burglary, and vehicle theft occur, there is a one hundred percent certainty that a robbery will happen.

Previously listed rules are present in the association rule table; lower confidence value does not support a high-level pattern reliability within the examined data. These results contained confidence values between seventy and eighty-three percent, with lift values that indicate the consequents are dependent on the antecedents, and the low confidence values moves the results into the probability level of certainty, indicating there is a chance the consequents still might not occur. From 2014 to 2015, there were four association rules that were present in both years' rule results. The first was homicide and narcotics, which are antecedents for assault in one to two percent of the census blocks with an eighty-two percent confidence rate carried over from 2013. The next rule present in both 2014 and 2015 crimes was robbery, car prowling, and homicide, these crimes are antecedents for assault. This association rule has been present in two percent of the census blocks and has a seventy-eight percent confidence value, which is an increase from 2014 by two percent. The next association rule present in 2014 and 2015 itemsets; is homicide, narcotics, and vehicle theft which are antecedents to assault in one percent of the census blocks studied. This rule has a one-hundred percent confidence value that is equal to the previous years' confidence value. The last association rule found in 2014 and 2015 was car prowling and narcotics, which are also antecedents to assault in two to three percent of the census block analyzed in this study. The confidence value for this rule is seventy-nine percent, which is down four percent from 2014.

Table 38 2015 Crime Association Rules

Antecedents	Consequents	Support	Confidence	Lift
Homicide, Narcotics	Assault	2-3%	82%	2.76
Car Prowling, Narcotics	Assault	2-3%	79%	2.65
Narcotics, Vehicle Theft	Assault	2-3%	75%	2.11
Narcotics, Vehicle Theft	Car Prowling	2-3%	75%	2.92
Car Prowling, Homicide, Vehicle Theft	Assault	1-2%	100% (**)	3.38
Car Prowling , Narcotics, Vehicle Theft	Assault	2%	89%	3.00
Assault, Narcotics, Vehicle Theft	Car Prowling	1-2%	89%	3.46
Burglary, Narcotics	Robbery	1-2%	88%	1.53
Robbery, Narcotics, Vehicle Theft	Assault	1-2%	86%	2.9
Robbery, Narcotics, Vehicle Theft	Car Prowling	2%	86%	3.34
Car Prowling, Narcotics, Homicide	Assault	1%	100%	3.38
Robbery, Car Prowling, Homicide	Assault	2%	78%	2.63
Robbery, Car Prowling, Homicide, Vehicle Theft	Assault	1%	100% (**)	3.38
Homicide, Vehicle Theft, Narcotics	Assault	1%	100% (**)	3.38
Assault, Burglary, Vehicle Theft	Robbery	1%	100%	1.75
Robbery, Car Prowling, Narcotics	Assault	2%	78%	2.63
Assault, Homicide, Vehicle Theft	Car Prowling	2%	78%	3.03
Narcotics, Vehicle Theft	Assault	2%	75%	2.53
Narcotics, Vehicle Theft	Car Prowling	2%	75%	2.92
Robbery, Homicide, Vehicle Theft	Assault	2%	75%	2.53
Assault, Car Prowling, Narcotics	Vehicle Theft	2%	73%	3.35
Homicide, Narcotics, Vehicle Theft	Car Prowling	1%	100% (**)	3.90

Note: (*) denotes Association Rules with a Confidence >= 93% but less than or equal to 99% and (**) denotes blocks of Confidence = 100%

5.2.2 2016 Association Rule Results

In 2016, the Apriori algorithm conducted twenty iterations and reviewed four-hundred and eighty-seven instances before generating the following strong association rules listed in the 2016 Crime Association Rules table, when analyzing the eight different types of crime. These are the association rules for crime in 2016, with a confidence value equal to or above ninety-three percent and the lift, value is high enough to support the consequents are dependent on the Antecedents:

1. In ninety percent of Seattle, census blocks, where robberies occurred, there is a ninety-seven percent certainty that assault will take place.
2. In ninety percent of Seattle census blocks, where car prowling occurs, there is a ninety-five percent certainty that a robbery will occur in this census block
3. In eighty percent of Seattle census blocks, where robbery and vehicle theft occurred, there is a ninety-eight percent chance that car prowling will happen in this census block.
4. In eighty percent of Seattle census blocks, where vehicle theft happens, there is a ninety-eight percent chance that car prowling will occur.
5. In eighty percent of Seattle census blocks, where homicide and narcotics crimes occurred, there is a ninety-four percent certainty that assaults will occur in this census block.
6. In eighty percent of Seattle census blocks, where car prowling and vehicle theft occurred, there was a ninety-six percent certainty that robbery would occur within that census block.
7. In eighty percent of Seattle census blocks, where homicide, narcotics, and vehicle theft occurred, there was a ninety-five percent certainty that assault would occur within that census block.

8. In eighty percent of Seattle census blocks, where vehicle theft occurs, there is a ninety-five percent certainty that a robbery will occur within that census block.
9. In eighty percent of Seattle census blocks, where robbery and car prowling occurred, there is a ninety-three percent certainty that vehicle theft will transpire within that census block.
10. In eighty percent of Seattle census blocks, where robbery occurs, there is a ninety-three percent certainty that vehicle theft will occur within that census block.
11. In eighty percent of Seattle census blocks, where car prowling occurs, there is a ninety-two percent certainty that vehicle theft will occur within that census block.
12. In fifty percent of Seattle census blocks, where assault and vehicle theft occur there is a ninety-nine percent certainty that car prowling will occur within that census block.
13. In fifty percent of Seattle census blocks, where assault, robbery, and vehicle theft occurred, there is a ninety-nine percent certainty that car prowling will occur within that census blocks.
14. In fifty percent of Seattle census blocks, where assault and robbery transpired, there is a ninety-eight percent certainty that car prowling will occur within census blocks.

15. In fifty percent of Seattle census blocks, where assault, robbery, and car prowling occur, there is a ninety-seven percent certainty that vehicle theft will occur within this census block.
16. In fifty percent of Seattle census blocks, where narcotics and vehicle theft occur there is a ninety-eight percent certainty that car prowling will occur within this census block.
17. In fifty percent of Seattle census blocks, where assault and robbery occur, there is a ninety-seven percent certainty that vehicle theft will occur within that census block.
18. In fifty percent of Seattle census blocks, where assault, car prowling, and vehicle theft occurred, there is a ninety-seven percent certainty that a robbery will occur within that census block.
19. In fifty percent of Seattle census blocks, where assault and car prowling occur, there is a ninety-six percent chance that vehicle theft will occur within that census block.
20. In fifty percent of Seattle census blocks, where assault and robbery occur, there is a ninety-six percent certainty that car prowling and vehicle theft will happen within that census block.
21. In fifty percent of Seattle census blocks, where assault and vehicle theft occur there is a ninety-five percent certainty that robbery and car prowling will occur within that census block.

The crime data itemsets for 2016 consisted of over six hundred potential association rules. This list was scaled down to the twenty-one strongest association rules. From 2015 to 2016, there were three association rules that were present in both years. The first was homicide and narcotics, which are antecedents for assault in eighty percent of the census blocks, with ninety-four percent confidence value; this rule was present across all four years results. Its' confidence value has decreased from 2015 to 2016, by three percent. The next association rule is homicide, narcotics, and vehicle theft, which are the antecedents of assault; this rule started in 2014, and has persisted throughout 2016. Support has fluctuated from one percent to eighty percent, while its confidence value in 2016, is nine-five percent, this rule is showing a decreased from previous years by five percent. The last persistent association rule originates in 2014, and persists to 2016. Narcotics and vehicle theft are antecedents of car prowling and the minimum support value for this rule has a range of one percent to fifty percent, with a confidence value of eighty-three percent in 2014, seventy-five percent in 2015, and ninety-eighty percent in 2016.

Table 39 2016 Crime Association Rules

Antecedents	Consequents	Support	Confidence	Lift
Robbery	Car Prowling	1-90%	97% (*)	1.02
Car Prowling	Robbery	1-90%	95% (*)	1.02
Robbery, Vehicle Theft	Car Prowling	1-80%	98% (*)	1.02
Vehicle Theft	Car Prowling	1-80%	98% (*)	1.02
Homicide, Narcotics	Assault	1-80%	94% (*)	1.69
Car Prowling, Vehicle Theft	Robbery	1-80%	96% (*)	1.03
Homicide, Narcotics, Vehicle Theft	Assault	1-80%	95% (*)	1.67
Vehicle Theft	Robbery	1-80%	95% (*)	1.02
Robbery, Car Prowling	Vehicle Theft	1-80%	93% (*)	1.03
Robbery	Vehicle Theft	1-80%	93% (*)	1.02
Car Prowling	Vehicle Theft	1-80%	92%	1.02
Assault, Vehicle Theft	Car Prowling	1-50%	99% (*)	1.03
Assault, Robbery, Vehicle Theft	Car Prowling	1-50%	99% (*)	1.03
Assault, Robbery	Car Prowling	1-50%	98% (*)	1.03
Assault, Robbery, Car Prowling	Vehicle Theft	1-50%	97% (*)	1.07
Narcotics, Vehicle Theft	Car Prowling	1-50%	98% (*)	1.02
Assault, Robbery	Vehicle Theft	1-50%	97% (*)	1.03
Assault, Car Prowling, Vehicle Theft	Robbery	1-50%	97% (*)	1.03
Assault, Car Prowling	Vehicle Theft	1-50%	96% (*)	1.06
Assault, Robbery	Car Prowling, Vehicle Theft	1-50%	96% (*)	1.09
Assault, Vehicle Theft	Robbery, Car Prowling	1-50%	95% (*)	1.05
Note: (*) denotes Association Rules with a Confidence >= 93% but less than or equal to 99% and (**) denotes blocks of Confidence = 100%				

6. DISCUSSION AND CONCLUSION

Crime is a persistent threat to most civilized societies, throughout the world. Currently, there is no universal solution to this problem; however, there are opportunities to reduce the density of crime. One key takeaway from this study is the presence of certain types of infrastructures, like bus stops and churches had a significant relationship with lower crime densities. My results proved this, and it is counterintuitive to most relevant literature on the subject matter of crime in society. The reason crime density reduction is counterintuitive, is the dominant trend in crime analysis is to research the root cause of criminal activity, not focusing on density reduction and prevention.

Previous literature often focused on elements that increase crime. Roncek and Bell (1981) found that city blocks with bars have significantly more violent crime than city blocks without bars. Ratcliff (2012) echoed these results, finding that violence clusters around bars dissipates rapidly at a distance of eighty-five feet, (Ratcliffe, 2012). Kubrin and Hipp (2011) showed that fringe banking options led to an increase in criminal activities, like larceny and assault, thereby, creating a high crime environment. Coccia (2018) investigated temperatures as a component of violent crime, determining that violent crime and aggressive behavior in society, was traceable to a combination of high temperatures and high socioeconomic inequality. My results-focused on infrastructure as a reducer of crime density.

6.1 Schools

Nordin (2018) demonstrated that educational institutions facilitated a decrease in both property crime and violent crime. This finding was mirrored by Hernandez (2017), who demonstrated that investment in early childhood education coincided with a reduction in violent and property crimes. My results for school in Seattle from 2013 to 2016 differed from both Nordin and Hernandez's research on the statistical significance of schools when analyzed against violent, crimes such as assault and robbery. When it came to homicide over the duration of four years, schools corresponded with a reduction of crime density in their surroundings. Schools proved statically insignificant when compared to overall surrounding crime density for violent crimes. This insignificance mirrored my results for property crimes such as bike theft, car prowling, burglary, vehicle theft, and narcotics crimes. A large component of this difference in results could be because of the sample size used; Nordin used schools from 287 municipalities in Sweden. In my study, homicide made up the smallest portion of crimes represented in the criminal database for Seattle. The school and homicide density significance relationship may be a by-product of the low number of homicides reported and not proof of a correlation of school's influence on the surrounding community.

6.2 Parks

The value that neighborhood parks add to a community has been a contentious question among researchers, when it comes to its relationship with criminal activity, the results from Groff and McCord (2012) and Brandon et al (2018) being both similar and divergent at times. Groff and McCord (2012) linked parks with increases of crime in the surrounding area, except in cases where they bordered places with mixed land use, that consisted primarily of commercial, institutional and residential properties. Brandon et al (2018) studied a green project on Chicago greenway trail and discovered that the creation of greenways and parks coincided with a positive effect on violent and property crimes. My results for parks vary greatly depending on the crime type. Leading to the assertion that my results were similar to both researchers. When it came to violent crimes, my results were similar to Brandon's: parks were highly significant when compared to the crime density of assaults around parks. My analysis of parks and violent crimes like robbery and homicide was not consistent. My findings for property crimes like car prowling, bike theft, vehicle theft, and burglary were insignificant. Parks did prove significant when it came to narcotic crimes over the four-years. My results were similar to Groff's research, with parks relating to some positive significances on assault and narcotics, but limited significance on other crimes. Geomasking of police reports to protect the identity of the victims could affect the crime density inside parks directly. This data approximation could account for why my results were different from Brandon and at the same time similar to Groff.

6.3 Bus Stops

Ridgeway and MacDonald (2017) researched the effects of rail transit on crime in Los Angeles, California from 1988 to 2014, thereby, discovering that rail traffic resulted in no increased crime for the surrounding neighborhood. Gallison and Andresen (2017) studied Ottawa, Canada's O-Train system crime data, and discovered that a train presence did lead to an increase in vehicle theft; the evidence did not support an increase in any other type of crime in the transportations systems. Spicer (2017) conducted research on Vancouver, Canada and focused on the cognitive fear of crimes that transportation hubs create; proving that societal fear of crimes around public transportation is a predominant limiting factor in the development of transportation centers. My research focused on bus stops throughout the city of Seattle and it proved that bus stops are highly significant, when analyzed for their relationship with crime density. Bus stops from 2013 to 2016 proved highly significant with all types of violent crime densities, like assault, robbery, and homicide. Bus stops even proved significant with almost all the property crime densities in this study, relating to bike theft, burglary, car prowling, and narcotics. All these crimes demonstrated a reduction in density around bus stops. Bus stops also had areas of significance when contrasted with, vehicle theft. The number was noticeably less when compared with the other type of crime from 2013 to 2016. My results mirrored Ridgeway's and Gallison's results, even though their results studied train transportation. This consistency suggests that transportation systems have a strong relationship with lower crime density.

6.4 Religious Centers

Crime and religious centers have always had a relationship from the sociological and criminal justice perspective. Adamczyk (2017) published results of a ten-year study taking place from 2004 to 2014, in New York proving that religion has a deterring influence on crime, but noted more research needs to be accomplished in the strengths and weakness of this deterrence. Salvatore and Rubin (2018) researched religious influence on criminal behaviors in adults within the United States, proving that religious centers are an influential component to reduce crime in adults. However, Salvatore and Rubin specified more research was required to confirm this deterrence component, leading this research to coincide with Adamczyk (2017) publication. Nicolae (2016) conducted a study on the role of Romanian churches in crime deterrence. It was discovered that the presence of these churches significantly diminished, overall crime rates in the surrounding areas. My results for religious centers showed these places of worship were associated with significantly lower rates of violent crime densities for assault and robbery. When compared with homicide, religious centers only appeared significant at fifty percent of distance bands. In addition, this inconsistent relationship occurred with vehicle theft and narcotics. When it came to property crimes such as bike theft, burglary, and car prowling, religious centers were consistently associated with significantly lower crime rates. My results varied from Adamczyk, Salvatore, and Nicolae, because I did not limit my religious centers to one dominant religion (Christianity), but a multitude of religious faiths, including all the religions centers stored in the Seattle database.

6.5 Emergency Stations

Emergency stations in this study acted as a control group, with limited literature assessing the relationship between emergency stations and crime. Several papers were published, about the association potential between criminal opportunities and emergency stations. Barak and Partridge (2016) studied hotspot policing in London, demonstrating that criminals operate within environmental boundaries, this gives the cause and effect approach, in which one commits a crime in their own area. Ratcliff and Taniguchi (2018) researched drug activity and gang violence referencing the theory of location denial. Location denial uses city planning to develop features in a community that have discouraging effects on specific types of crime, removing the likelihood of that type of crime, and creating an area of denial for that negative behavior (Ratcliffe, Taniguchi, 2008). Emergency stations served as a control point for emergency response, they represented government entities that are not directly linked to law enforcement, could exhibit similar effects that mirror hotspot policing. When it came to significance testing on violent crime density from 2013 to 2016, emergency stations had distances that were significant. These small groups of significant relationships were not enough to prove overall significance on crime density, for the years tested in this study. When analyzing violent crimes like assault and robbery; emergency stations only proved significant when analyzed against homicide density. Emergency stations also proved insignificant when compared with narcotics and property crime density, like bike theft, burglary, vehicle theft, and car prowling. When looking at my results in comparison with Barak and Partridge (2016) conclusion on the concept of dispersion, which states when criminals suspect an area is monitored, they will seek other areas and opportunities. My results for emergency stations are similar to Barak, because emergency stations are known government entities that have an affliction with law enforcement, meaning they act like police patrols for hot spots. My results also did not align with Ratcliff's theory of location denial, because my testing did not produce similar results on crime significance. This precipitated my rendering emergency station land-use mostly insignificant on crime density for the four-year duration of this study. Emergency stations are areas that could have long-standing benefits for their communities, due to fact they serve as quick response units to the medical needs of the surrounding areas they service.

6.6 Association Rules for Seattle Crime

The use of data mining for association rule generation is not new to criminology. Rathlee et al (2016) presented the results of how an improved association rule mining could help predict the most crime-prone areas in a city, or predict the criminals that are most likely to be repeat offenders. Sevri et al (2017) used association rule mining on criminal records, throughout the United States to support law enforcement by identifying relationships between new crimes and old incidents and even predicted the perpetrator ethnicity, based on association rule antecedents. My results for crime pattern analysis, using the association rules derived from the Apriori algorithm during the time of this study from 2013 through 2016, were similar to Rathlee and Mehmet. The reason for the similarity is the application of Apriori algorithm. The goal was to produce and clearly define association rules that could assist law enforcement, in better policing and understanding crime patterns in data.

The strongest association rules from my analysis were for crime and census block data, using the Apriori algorithm. There were two rules that persisted throughout most of the years studied. The first association rule was in the census blocks where law enforcement discovered narcotics crimes and homicide, there is an eighty to ninety percent certainty that an assault is occurring within this census block. This pattern of criminal activity persisted all four years of the study. In terms of criminal behavior, this means that narcotics trafficking in Seattle, leads to violent crimes in most cases. This would explain why homicide collocates with narcotics and almost guarantees the occurrence of an assault, which could be a by-product of criminally failed homicides. The second association rule that occurred in the data and produced a pattern from 2014 to 2016, was in census blocks with narcotics, homicide, and vehicle theft, there is a ninety-five to one-hundred percent certainty that assault is happening in these census blocks. By refining and developing association rules for multiple types of crimes, law enforcement can strategically target crimes and seek to obtain a predictive position on enforcement by knowing what they are looking for when hotspot policing.

6.7 Future Consideration

I have proven that specific types of land use are associated with lower rates of crime density. This result does not eliminate the need for law enforcement; rather it seeks to enhance communities' preventive influence by demonstrating the importance of existing features in the development of a preventative geospatial solution. Association Rule mining can be used by law enforcement, in establishing predictive trends of crime patterns, not just based on hotspot policing but by what crimes are occurring, and what is likely to occur based on statistical pattern analysis. This approach to predictive policing can eliminate dispersion created by hotspot analysis, allowing police to target crimes they have certainty is occurring within that area. My research focus was Seattle, Washington; however, both of the analysis methods used, can apply to any geographic location or infrastructure. One important consideration for future analysis is better crime data. The 2013 to 2016, crime data used in this study was not a precise location due to geomasking. This geomasking adjustment could have influenced the significance testing.

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BIOGRAPHY

Ryan G. Delts graduated from the University of North Carolina Wilmington and received his Bachelor of Science in Computer Science in 2006. He was recruited by the Department of the Army as a Quality Assurance Specialist and Site Planner. It was during this time he developed an interest in Geographic Information Systems (GIS) this interest inspired him to transfer to the Washington, DC metro and work for the Army Corps of Engineers Geospatial Research Laboratory (GRL). During his time as an employee of the GRL, he has supported the Department of Defense working on the planning and strategic mapping tool creation. Mr. Delts is currently working on completing his Masters in Geospatial Intelligence and a member of Upsilon Pi Epsilon, Computer, and technology honor society. He is employed as a scientist and configuration manager with the federal government.