Creating Hot Streets: Developing an Automated Approach Using ModelBuilder

by

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A Thesis Presented to the
Faculty of the USC Graduate School
University of Southern California
In Partial Fulfillment of the
Requirements for the Degree
Master of Science
(Geographic Information Science and Technology)

December 2018

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This paper is dedicated to my family and friends who provided me with constant support throughout my schooling process, and to all the teachers and professor who have trained me to this point for always believing in me.

Acknowledgements

I am grateful to my supervisor, Dr. Laura Loyola, for all the guidance, belief, support, and motivation provided to me during the thesis development and writing process. I also appreciate the guidance provided by the other thesis committee members Dr. John Wilson and Dr. Yao-Yi Chiang. I am thankful to my parents Sir Engr Erefaa and Queen Tom-Jack, my siblings, and God for providing the opportunity to attend this institution. I would also like to thank the tactical crime analysts Glenn Grana and Robert Petersen who shared some of the information needed to develop this thesis. With a special mention to some of my graduate and undergraduate professors Dr. Jennifer Swift, Dr. Jacque Kelly, Dr. Fredrick Rich, Dr Kelly Vance, Dr. James Reichard, Dr. Charles H. Trupe, It was terrific to have the opportunity to attend your classes, and perform some research alongside which solidified my experience and confidence to perform this research.

List of Abbreviations

ARC	Atlanta Regional Commission
CL	Confidence Level
CPM	Crimes Per Mile
CPTED	Crime prevention through environmental design
GIS	Geographic information system
GISci	Geographic information science
GIST	Geographic Information Sciences & Technology
HSA	Hot Street Analysis
IACA	International Association of Crime Analysts
LEA	Law Enforcement Agencies
MAUP	Modifiable Areal Unit Problem
NYPD	New York Police Department
OSM	Open Street Map
PCS	Projected Coordinate System
USGS	United States Geological Survey
USC	University of Southern California

Abstract

The creation of Hot Streets can positively influence the crime reduction efforts by law enforcement agencies (LEAs) by decreasing patrolled Hot Spot areas and more directly focusing efforts at the street level. As there has been no easy way of determining Hot Streets, police officers patrol general areas that vary in size and difficulty of patrol. The purpose of this study is to create a model within a GIS, particularly ArcGIS Pro, for all users who wish to accurately and efficiently analyze crime patterns on a street level. The model shows all users, especially the LEA tactical analysis department, a simple but effective means of using a GIS to improve current spatial crime analysis methods by the addition of Hot Streets. This study demonstrates how to analyze and automate the creation of Hot Streets within the ModelBuilder pane for the city of Atlanta, Georgia. The research provides users with places for the acquisition of GIS data, methods and input parameters required for processing data prior to incorporation in the model as well as within the model, and the proper sequence of tool utilization for analysis within the model. This process resulted in Hot Street maps with several streets classified based on the crime cluster confidence levels of 90% and above for the city of Atlanta. The Hot Street provides results for seven confidence levels; which include high and low value crime clusters at 90%, 95%, and 99% respectively, and a final group of streets without a significant cluster. The developed model was found to be an excellent tool in analyzing crime patterns on a street level and creating the Hot Street maps at different scales. Both LEAs and civilians can utilize the developed Hot Street implementation, as it provides a way to reduce crimes through hot street policing and crime prevention through environmental design.

Chapter 1 Introduction

Crime, like any other event, always occurs at a particular place and time. Geographic Information Systems (GIS) have been used by Law Enforcement Agencies (LEAs) to help their crime analysis divisions visually represent and understand crime patterns over space and time. Based on a variety of crime theories, there are several methods one can employ for crime analysis which aid in crime reduction efforts by LEAs, especially within high crime areas. Geospatial crime analysts currently use spatial analysis and statistic tools to perform crime analysis and determine the high crime areas. Authors on the subject have mainly concentrated on mapping crime point density, kennel density, hot spot, Hot Spot, and heat maps; while finding correlations with the help of R and R-ArcGIS Bridge, or other statistical software integrated with ArcGIS (e.g., Scott and Warmerdam 2017; Trepanier 2014; Bruce and Smith 2011; Boba 2005). One of the most popular methods of the listed techniques is Hot Spot (upper case) analysis, which are areas that suffer from statistically significant clusters of crime. As a few streets contain the majority of crime in negatively affected neighborhoods, most studies conclude that patrols of Hot Spots in those neighborhoods and the remainder of the city have resulted in reductions in crime (Braga et al. 2012; Schnell et al. 2016). Although the current methods fulfill their goal of visually representing crime occurrences and helping LEAs and civilians be aware of what is happening around them, they are lacking in a more accurate representation when studying crimes on the street level.

Currently, police officers patrol general areas, as there has been no easy way of delineating linear hot spots also known as hot streets (Eck et al. 2005). Hot Streets are resultant crime clusters analyzed with statistical proximity relationships at the street level. In this document, a hot spot/ hot street (lower case) refers to the general term of identified crime clusters with no spatial statistical backing, while a Hot Spot/ Hot Street (upper case) is a result of spatial statistical output. Based on the reviewed literature there is only one methodology that has been published on developing Hot Streets with the same Getis Ord Gi* statistic used for Hot Spot analysis (Brazil et al., 2017). One problem with the spatial analysis in the published methodology is that it uses Euclidean distance rather than the actual road network to assess Hot and Cold Streets. Different crime areas separated by a river or a major highway might be close together as the crow flies (Euclidean distance), but far away from each other on a road network with few bridges or underpasses (Esri, 2018b). Since the Hot Spot analysis tool is looking for high crime rates that cluster close together, accurate connectivity is essential. None of the reviewed papers for determining a Hot Street account for the adjacent street crime values, the same way the area Hot Spot analysis takes account of nearby connected crime clustered areas when selected. This information is essential because crime concentrates at a micro-scale / minimal units of geography (Weisburd et al. 2012; Weisburd et al. 2015), and with changing policing patterns, crime is not stagnant and can migrate to nearby regions. Hot Streets can provide the missing high level of precision for observing crime patterns on each street. As seen in several examples (e.g., Eck et al., 2005; Trepanier, 2017), most of the current street analyses of crime patterns include the use of total crime count by street symbolized with graduated symbols, graduated colors, and point density raster attachment, but none of these methods provide statistical relationships between connected roads. Thus, the current methods do not meet the definition of Hot Streets within this document and the needs to have Hot Street analysis available.

This study demonstrates an effective way of depicting Hot Streets within the city of Atlanta, Georgia with the use of a GIS. The primary research goal is to add to the current literature on crime analysis that utilizes a GIS by applying the use of the Getis-Ord Gi* statistic, used in the generation of Hot Spot areas, to developing Hot Streets. The Getis-Ord Gi* statistic delineates statistically significant spatial clusters once the crimes are attached to the nearest streets. This research will present an automated model for the achievement of the set goal, enabling people of all experiences and levels to perform the analysis. Within the police department this analysis will be performed by tactical crime analysts who may or may not have a geospatial degree. Both LEAs and civilians with basic GIS knowledge can efficiently utilize the Hot Streets methodology developed from this research; the results of which will provide an effective way to reduce crimes through whatever recommendations are provided by the administrative crime analysis department. Example of recommendations include Hot Street policing, and increased civilian safety by keeping them away from or making them aware of dangerous streets during their commutes. The end test result for a successful model is an overlay of the identified Hot Streets and a currently used high crime detection method such as the kernel density, in order to see the similarity between results from a point area analysis to a linear street analysis of crime distribution and also any increase in specificity.

1.1. Motivation

The enhancement of the Hot Street Analysis (HSA) and use of the HSA within a GIS is the principal goal of this research. The motivation behind this is to assist tactical analysis teams with a more in-depth and geographically localized result. To achieve the goal (or aim), spatial statistics that account for street connectivity are added to current Hot Street procedures. The Hot Streets not only allow more direct and safer navigation through or away from Hot Spots, but the enhancement of Hot Streets also provides precise patrol route possibilities for LEAs. These enhanced patrol routes can result in improved crime reduction efforts, and in return keep the civilians within the city safer.

GIS tools can help to improve navigation within or past Hot Spots through the creation of Hot Streets. Currently, only Hot Spots are developed within ArcGIS with the use of Getis-Ord Gi* (Esri 2018). Hot Spot policing has resulted in noteworthy crime reduction through police concentration in smaller crime areas (Braga et al. 2012; Grana and Windell 2016), and policing these Hot Spot areas is mostly done with vehicles. However, this form of analysis is not helpful for navigational purposes because no work to date has reclassified Hot Spot data to the streets within the Hot Spot areas. There is a need to be able to replicate the creation of Hot Spots to a street level as Hot Streets that both the police and civilians travel on. The resulting method would result in safer travels for civilians, more precise street segments within regions for patrol, reduced crime along the streets within those Hot Spot areas, and a replicable method for all crime analysis departments for Hot Street Policing. Civilians would have a more positive commuting experience because of this research, as they will be more spatially aware of the potential threats along their routes.

This work contributes to studies on the creation of hot streets. Hot street creation often happens on a neighborhood level, as it is used to direct patrol routes in dangerous neighborhoods (Gwinn et al. 2008). The Hot Streets created in this work can be used on multiple levels to examine street-level relationships of crime through high and low clusters via Z-scores and P-values that help display spatial clusters of high and low crime streets.

This study will attempt to create a standardized model that all police departments and civilians in different cities can adopt. Though various issues, such as how many nearby streets should influence a single linear segment calculation, may result in slight changes to the developed Hot Street Model in different regions. This model will help simplify the process of identifying Hot Streets so that any user can apply this crime analysis for tactical purposes. The research will also aid police and civilians to import data into a GIS and to process the data into meaningful information. Finally, it builds the capacity of police departments to use GIS as a tool to serve their civilian population. The model tool can serve the population through the generation of specific street names with crime clusters which provide the chance for residents to take personal action in increasing personal safety via home fencing, surveillance, etc.

1.2. Questions

Developing a Hot Street Analysis (HSA) model to aid current studies and applications of crime and street relationships comes with its own set of questions and considerations. These include the modifiable areal unit problem (MAUP), tool availability, design and effectiveness, and replicability.

The MAUP occurs because different aggregation schemes yield different results despite using the same analysis and data. Despite this problem, the different results are often valid as different analyses seek to answer different questions on a variety of scales (Esri 2018a). According to Brazil et al. (2017) because smaller units (streets) are more homogeneous, they can be better measures of environmental characteristics. This means that the results which are valid for the street level crime study may be more accurate than broader area aggregation techniques.

There are several tools developed within a GIS for specific purposes. Within a ModelBuilder pane in ArcGIS Pro, these tools can be combined to accomplish significant tasks requiring the acquisition of tools. Hot Street creation is an example of one of the tasks that requires multiple tools to work within ModelBuilder, and fortunately, the needed tools and add-ins are all available with the appropriate extensions in Esri’s ArcGIS platforms.

Designing the model also requires a process of measuring the full effectiveness of each individual tool selected and the proper order in which these tools are utilized. Within the ModelBuilder there will need to be decisions made on whether the individual tools achieve the desired outcome and where the tool can be improved, either through setting different parameters or the addition of subsequent tools. The intention of building this model is to replicate this process so that it can enhance Hot Street Analysis.

As a result, the question of replicability comes up. With slightly different data inputs, care will have to be taken to ensure anyone in any city can pick and use the model on the fly. This research will determine if the developed model can be used to accomplish all the listed goals within a study area different from that in this research through making sure that all the input model parameters can be used for any study area and testing on an additional (secondary) dataset.

1.3. Study Area

This research will develop its model with data from the city of Atlanta, Georgia because of the author's proximity to the police department, current contacts with the Tactical Crime Analysis Unit, and familiarity with the environment. The city of Atlanta (Figure 1) is the capital of the state of Georgia and is situated within two different counties: Fulton and Dekalb counties. The city covers 133.9 square miles of which only 0.63 percent is covered by water. Atlanta is currently the ninth largest metropolitan area in the US with over 5.7 million people, and currently has over 2,000 sworn police officers, making Atlanta's Police Department the largest law enforcement agency in the state of Georgia (City of Atlanta, 2018). The city is home to a diverse population, with varying income levels throughout the city.

Figure 1. Map of Atlanta, Georgia

1.4. Thesis Outline

The remainder of this thesis begins with a literature review, followed by the presentation of the methodology used to develop the model within ModelBuilder, the results, a discussion of findings and comparisons to other crime analysis, and a conclusion.

Chapter 2, reviews related literature on current cluster analyses and uses. The current methods of Hot Spot analysis will be explained in detail since this informed the choice of methods for the generation of crime Hot Streets. Literature supporting the development of the model is introduced, as well as a brief explanation of the statistics.

In Chapter 3, the developed methods used in creating Hot Streets are discussed. The chapter presents the model for the HSA with the supporting documentation for the use of each tool. The chapter also lists required data inputs and the best sources to yield needed results.

Chapter 4 presents the final HSA model and results of the multiple and varied model runs. The resulting street layer should display the statistically significant crime clusters by street. These results are presented with kernel density outputs as well to verify and compare Hot Street crime clusters to a traditional method of crime visualization.

Chapter 5 interprets the significance of the results, and how they compare to other crime analyses currently performed. The chapter explains in detail how the results fulfill the goals of the project, provides additional insights into the model, as well as possible adjustments that could affect the results. This chapter also provides conclusions based on the importance of this research and the ability of crime analysts and police to determine Hot Streets.

Chapter 2 Background

Developing a Hot Street Analysis (HSA) for spatial crime analysis requires knowledge of several topics in both crime analysis and GIS. To understand the process and purpose of this analysis, anyone who intends to use this method must understand the history and different types of crime analysis, the current methods of crime mapping with geographic data, and the benefits of Hot Streets compared to other current methods.

2.1. Crime Analysis

Crime Analysis is a process of analyzing data via qualitative and quantitative methods for use by all police agencies and their communities, especially within the International Association of Crime Analysts (IACA) (IACA, 2014). The practice of crime analysis has been performed since the nineteenth century or earlier, but made huge advancements in the 90's after the New York Police Department (NYPD), for the first time in history, began guiding law enforcement efforts based on crime statistical results generated from the computerized mapping program CompStat (Grana and Windell 2016; and Horowitz 2013). LEAs around the country embraced the innovation after the NYPD reported a 12% decrease in crime during the first year, and additional significant decreases in crime in every district in subsequent years (PERF 2013). Currently there is a two-part classification of crimes. Part I offenses which are used in current mapping programs include eight crime types, namely: criminal homicide, rape, robbery, aggravated assault, burglary, larceny, auto theft, and arson. Since Part II offenses have no spatial information for a majority of the data, most crime studies use Part I crimes for crime pattern identification.

Crime analysis has grown to encompass different processes and techniques at several levels with the adoption of CompStat and other newly designed computer programs by various police departments. According to the IACA (2014), the assignment of crime analysis functions is divided into four significant classifications which are sequential based on the data sources, the analysis techniques, the results of the analysis, the frequency and regularity of the analysis, and the intended listeners and purpose. The recognized classifications of crime analysis include 1) crime intelligence analysis, 2) tactical crime analysis, 3) strategic crime analysis, and 4) administrative crime analysis. The principal goal of employing different analyses is the efficient and effective running of police departments to reduce crime (Grana and Windell 2016). The next section further differentiates these four types of crime analysis, while Section 2.1.2 specifically relates tactical crime analysis to crime mapping.

2.1.1. Types of Crime Analysis

There are four major types of crime analysis, but the definitions are not mutually exclusive and there remains overlap in the respective purposes of the different forms of analysis. The definitions presented in this section provide the fundamental differences highlighted by current crime analysts for the proper distinctions between classifications. The first type of crime analysis called crime intelligence analysis is a qualitative analysis that aims to contextualize data about the people (offenders or victims) repeatedly involved in crimes, criminal organizations, and/or networks (IACA 2014, Santos 2016). The processes and techniques for this type of analysis include 1) repeat offender and victim analysis, 2) criminal history analysis, 3) link analysis, 4) commodity flow analysis, 5) communication analysis, and 6) social media analysis (IACA 2014).

Tactical crime analysis is mostly a quantitative analysis that deals with the daily identification and analysis of emerging and existing short-term crime patterns (Grana and Windell 2016; and IACA 2014). This type of analysis provides police officers the ability to allocate resources efficiently based on the resultant the crime patterns, trends, and potential suspects retrieved from the analysis (Grana and Windell 2016). Efficiently allocating resources is possible in accordance with the 6/68 rule which states that there are a small amount of offenders (6%) that commit the majority of criminal activity (68%) and the findings of Weisburd et al. (2016) from an accumulated study that crime is concentrated at a small number of places spread widely across the city. The overall goals of tactical crime analysis include the immediate identification of crime patterns and analysis of patterns to identify potential suspects of a crime or crime pattern (Boba 2001) and the processes and techniques used in tactical crime analysis include 1) repeat incidence analysis, 2) crime pattern analysis, and 3) linking known offenders to past crimes (IACA, 2014). The results produced from the HSA fall within the tactical crime pattern analysis technique. Tactical crime analysis will be discussed further in the next section.

Strategic crime analysis is the next step taken after the short-term tactical crime analysis, as it combines both quantitative and qualitative analysis geared at examining information to identify and track long-term issues. It is important to examine long-term issues to aid in the development and evaluation of crime strategies, policies, and prevention techniques (IACA, 2014). The processes and techniques involved in strategic crime analysis include 1) trend analysis, 2) hot spot analysis, and 3) problem analysis.

Administrative crime analysis relates to the administrative responsibilities of the police agency, city government, and citizens. These responsibilities include appropriate planning, workload calculations by area and shift, community relations, budgeting, grant applications and many other areas that are not solely administrative tasks but involve analysis (IACA 2014). This analysis aggregates the other types of crime analysis to primarily inform audiences of all groups, which include police executives, city council, and civilians (Grana and Windell 2016). The processes and techniques include 1) districting and re-districting analysis, 2) patrol staffing analysis, 3) cost-benefit analysis, and 4) resource deployment for special events (IACA 2014).

2.1.2. Tactical Crime Analysis and Crime Mapping

Tactical crime analysis is a level of analysis which answers the questions of who, what and where of crime to help the LEAs identify crime patterns and gain a better understanding of crime (Grana and Windell 2016). It is one of the two primary and broad functions of crime analysis that involves the detection of patterns, linkage analysis for suspect-crime correlations, target profiling, and offender movement patterns (Canter 2000). This form of analysis entails 1) identifying emerging crime patterns, 2) carefully analyzing the identified crime patterns, 3) notifying the police department or agency about the identified pattern, and 4) working with the police department or agency to address the identified pattern (Grana and Windell 2016).

2.1.2.1. Crime Pattern

Crime patterns, crime trends, crime series, crime problems, hot spots, and so forth, have been used interchangeably in criminal literature before the IACA provided definitions which highlight the differences. A crime pattern is defined as a group of two or more crimes which are reported or discovered by the police and abide by certain conditions which make them unique (IACA 2011). The five unique conditions include:

1. They share at least one commonality, which can be crime type, location, the behavior of involved individuals, and so forth;

2. There is no recognized relationship between victim(s) and offender(s) (i.e., stranger-on-stranger crime);
3. The shared commonalities make the set of crimes notable and distinct from other criminal activity occurring within the same general date range (i.e., weekly; or monthly);
4. The criminal activity is occasionally of short-term duration, ranging from weeks to months; and
5. The set of related crimes is treated as one unit of analysis and addressed through focused police efforts and tactics (IACA 2011).

A crime pattern is more simply defined as a type of crime problem which is a repeated set of related harmful events in a community that the residents expect the police to address (Clarke and Eck 2003). A crime pattern also exhibits a few characteristics that do not make it a chronic issue: 1) it covers a shorter time span, 2) it is limited to a specific set of reported crimes, and 3) it has a routine-oriented operational tactical response carried out by the appropriate police agency in the jurisdiction.

It is essential to explain what a crime pattern is not, given the recent standardized definition which clarifies past confusions for the proper application of the term. The most important thing a crime pattern is not is a crime trend. People usually confuse a pattern for a trend and vice versa, but a trend only deals with changes over the long-term. The data changes can inform the police and the general public of the crime count changes, but since it does not examine shared similarities, it is not a crime pattern (IACA 2011).

2.1.2.2. Types of Crime Patterns

The IACA identified seven different types of crime patterns that meet the five conditions stated earlier. The crime patterns listed in this section are considered to be independent on their own, but they still contain a decent volume of overlap and are not always mutually exclusive. Due to the varying amounts of overlaps in the different types of crime patterns, a crime analyst has to gain an in-depth understanding of each of these to compensate for the existing ambiguity in the different crime patterns. A good understanding is also essential to categorize any pattern that is discovered to the most applicable pattern type based on the crime characteristics and the nature of the most appropriate potential police response (IACA 2011).

The seven primary crime pattern types are:

1. Series: A group of similar crimes thought to be committed by the same individual or group of individuals acting in concert. Example: Seven incidents have occurred over a 1-month stretch, and the suspect in all situations has the same description, method, and escape vehicle.
2. Spree: A regular set of crimes that appear continuous, and are carried out by the same individual or groups. They are characterized by high frequency of criminal activity within a short time frame. Example: Multiple armed robberies at different gas stations within an hour.
3. Hot Prey: A group of crimes committed by one or more individuals, involving victims who share similar physical characteristics, engage in similar behavior, or both. Example: Fifteen email scams targeting wealthy, single, elderly Americans in a week.
4. Hot Product: A group of crimes committed by one or more individuals in which a unique type of property is targeted for theft. These are thefts of products deemed attractive to

thieves (Clark 1999). Example: Theft of ninety high-end graphics cards within a handful of days.

5. Hot Place: A group of similar crimes committed by one or more individuals at the same location. Example: Three cases of aggravated assault in a motel within two weeks.
6. Hot Spot: A group of similar crimes committed by one or more individuals at locations in proximity to one another (IACA 2011). Examples: Ten daytime burglaries over the past four weeks at a suburban residential subdivision, with no notable similarities in the method of entry or known suspects.
7. Hot Setting: A group of similar crimes committed by one or more individuals that are primarily related by type of place where crimes occurred. Example: Twelve thefts from commercial vans parked in industrial neighborhoods with low lighting over two weeks.

2.1.2.3. Identifying Emerging Crime Patterns

Pattern detection occurs when offenses are reported promptly and accurately for the crime analysts to be able to identify common attributes among these offenses (Grana and Windell 2016). The standard attributes analyzed include the type of crime, time, method, and weapon type. Crime patterns can occur on varying scales which range from nationwide to neighborhood or smaller geographic levels. When a crime pattern occurs in a relatively small area, it is referred to as a “hot spot” or cluster (Grana and Windell 2016).

The tactical analysis of crime patterns is the primary responsibility of crime analysts at police agencies around the United States and other nations worldwide (Grana and Windell 2016). Crime analysts search databases on a daily basis and mine data to link cases by a variety of common attributes, they then distribute the information about known and newly discovered patterns to the appropriate personnel (Grana and Windell 2016). The analysis improves the safety of communities by shortening police response times and increasing police presence in high crime areas, which can reduce and prevent crime.

Effectively illustrating the hot spot crime patterns on a map means a crime analyst should understand the available methodologies and utilize them for different scales of analysis. Eck et al. (2005) suggest that crime analysts start the search for hot spot crime patterns by plotting points on small-scale maps, before the examination at larger scales of geography because of point overlaps. After using a preliminary visual analysis to search for clustered points, incidents of varying counts and ranges can be represented using different graduated symbols/colors (Paynich & Hill 2010). This next step of creating a descriptive map through the use of thematic mapping options is a common method of displaying statistically summarized data to get a more accurate picture of the overall distribution of crime (Santos 2016; Eck et al. 2005). Following the descriptive mapping is a form of standard deviation and density mapping analysis. Standard deviation mapping shows point clusters generated by random chance (Paynich & Hill 2010), and density mapping uses cells of different radius to perform mathematical functions for surface estimations which clearly show crime intensities in places containing many overlapping points (Harris 1999).

Once crime patterns are identified and mapped, they are communicated to police agencies via a bulletin. The bulletin describes in detail, the critical elements of the crime pattern and highlights any necessary implications for action. More specifically, crime pattern bulletins naturally include analytical elements such as a geographic profile, a temporal profile, suspect lists matching physical, modus operandi (M.O.) descriptions, or other information of investigative or prescriptive response value (IACA 2011).

2.2. Spatial Statistics for Clustering

For the hot streets to be a significant means of crime analysis like the Hot Spots, it has to utilize a GIS and apply statistical tests (National Institute of Justice 2010). There are several ways to apply statistics to find spatial clusters, e.g., Moran I statistics, Geary's C, Getis-Ord Gi, and Getis-Ord Gi* (Eck et al. 2015; Bruce et al. 2011). Careful consideration needs to be made in selecting a particular statistic, as methods such as the Moran's I (either general or local) cannot tell if the clustering is made of high or low values, it can only sense the presence of similar clustered values (Chang 2014). The inability of Moran's I to identify non-similar (high vs. low) cluster values and the necessity for such an analysis resulted in the use of the Getis-Ord Gi* statistic that takes account of neighboring features to locate where high and low values cluster spatially and show local dependence (Getis and Ord, 1993).

Hot Spots are currently created within an ESRI GIS environment using z-scores and p-values after calculating Getis-Ord Gi* statistic (Esri 2018). The Gi* statistic is used in this study because it enables the detection of local pockets of dependence not revealed using Moran's I statistic alone (Getis and Ord 1993). Ord and Getis (1995) expanded on the created spatial statistic (Getis and Ord 1993) to show how the mathematics accounts for the distance weights. The formula which is like that of Figure 2, was suited to study local patterns in spatial data and was initially tested with AIDS data and outbreaks which proved very useful in creating accurate Hot Spots.

The Getis-Ord local statistic is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}} \qquad (1)$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \qquad (2)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\bar{X} \right)^2} \qquad (3)$$

The G_i^* statistic is a z-score so no further calculations are required.

Figure 2. Gi* statistics formula. Source: Esri 2018

Monzur (2015) explained the calculations using the Gi* statistic in step by step order, which revealed the possible application at street level under a fixed distance analysis, where connected roads are analyzed for each road crime cluster value. Following the traffic accident analysis and mapping from Esri (2018b), it was proven that the Hot Spot tool within the Esri GIS platform could generate both area Hot Spots and linear Hot Spots, which are the same as the Hot Streets. Given the proven accuracy of using the Hot Spot analysis tool from area to street specific calculation, it presented the opportunity to create the Hot Streets automatically with a tool already in the GIS.

2.3. Hot Spot Policing

Hot spot policing has become a common way for police departments to prevent crime (Braga et al. 2012). Weisburd et al. (2001) explained that in a national survey of police departments with over 100 officers, 6 in 10 departments reported using crime mapping to visually identify crime Hot Spots for concentrated efforts. The following sections provide background on advances and advantages of Hot Spot policing as well as the development of Hot Streets for policing efforts.

2.3.1. Advantages of Hot Spot Policing

Over the recent years, the results of studies suggest that when police focus on smaller areas where crime is concentrated, they are more efficient at tackling criminal events (Grana and Windell 2016). The systematic review of Hot Spot Policing, showed adequate support for the assertion that focused police efforts on hot spots can be effective in preventing crime (Braga 2008; Braga et al. 2012; Eck 1997, 2002; Skogan and Frydl 2004; Weisburd and Eck 2004). After a review of crime analysis research, Braga et al. (2012) concluded "20 of 25 tests of hot spot policing interventions reported noteworthy crime and disorder reductions." The most extensive practical tests came back with up to a 75% reduction in motor theft within the study area. Braga et al. (2012) also discovered that not only did Hot Spot Policing have a positive effect on lower crimes in the area, it also had a positive effect on the community by creating a safer environment.

Telep and Weisburd (2016) analyzed 17 systematic reviews of policing performed over a time span of more than 13 years. Systematic reviews are relevant because they have proven to provide an assured test of strategy effectiveness, which is an essential resource in academia, criminology, and police practitioner interests (Telep and Weisburd 2016). From these reviews, they concluded that most of the effective policing strategies regarding crime control concentrated on small geographic areas (e.g., hot spot policing). Telep and Weisburd (2016) also realized that converging on a high crime street segment will not just push that hot spot to the next street block but would most likely cause a diffusion of the crime to nearby areas. This movement of crime to nearby areas is what makes the Gi* statistic discussed earlier in section 2.3 is very important, as the results for Hot Streets will reflect crime values in relation to nearby areas (streets) that crime can possibly migrate along.

2.3.2. Current Development of Hot Streets for Hot Spot Policing

There are several techniques used for the identification of hot spots for policing since no single method is sufficient (Eck et al. 2005). Given that most policing is performed while patrolling in a vehicle, the development of Hot Streets that tell the officers exactly where to go is significant. Within this instance, hot streets which are referred to from past literature, do not have any statistical backing and as a result, do not meet the definition provided earlier in this documentation. IACA (2013) discusses the strengths and weaknesses of various crime mapping techniques, and it explains how the current development of hot streets is performed by using total crime count per street after attaching the points to the nearest linear feature. It shows that the hot streets are then displayed with graduated colors (these hot streets do not meet the statistical requirement based on this documents definition). Eck et al. (2005) explain the limitations of this method of creating of hot streets as the fact that it was not a straightforward process, and it would be easier to use dot maps for their identification as most clustering algorithms only show area. Trepanier (2014) presented an interesting approach by using the raster resulting from the point density, to group the linear networks by crime intensity. The exact methods of doing so were not explained in detail for streets, which fell under different point density classifications. This work fills the knowledge gap of hot street development through the addition of a clustering algorithm that adds spatial statistical values, and automation of the entire process for ease of creation for patrols.

Chapter 3 Methodology

This chapter discusses the data, and rationale for the developed Hot Street methodology. Within this chapter is a detailed explanation of the different data acquired and the variable data types for the model inputs. After the explanation of the research design, there is a list of data with a discussion of the fitness for use and processing, before showing the created model.

The primary objective of this project is to create an effective way to allow any user to accurately represent statistically significant Hot Streets, which previously have proven difficult to analyze (Eck et al. 2005). The results of this analysis are necessary for reducing the crime occurrences on dangerous streets, by showing the police departments streets on which they should concentrate their efforts. The modeling of crime Hot Streets incorporates established methods and newer analysis techniques that require a wide variety of geoprocessing tools. These methods formulated after a critical review of relevant literature and informed the development of the model outlined in this section. The study utilizes spatial data for the model inputs that only needed a little refinement.

This chapter is subdivided into four sections. The first section elaborates on the research design and methods acquired from previous researcher. The second section lists out the data selected and their sources while diving into the fitness of use and preprocessing needs. The third section presents the flowchart and model that can be replicated to create Hot Streets automatically.

3.1. Research Design

Early crime street mapping techniques, recommendations from previous research, and case studies of point to polyline mapping to present a hot street shapefile are the building blocks of this research design. The first step of this thesis project is the combination of the crime points to the street segments. One recommended option is to plot crime incident locations on a map and match them to the nearest street layouts based on an approximate distance (IACA 2013; Grana and Windell 2016). After joining the points to the street segments, there will be a count of points per street segment. This work builds upon crime mapping on a street level by calculating total crime count per mile of street to account for different street lengths, instead of using only crime counts per street. The additional calculation to normalize crimes per mile is crucial because different streets have different lengths, and smaller streets would most likely have fewer crimes and vice versa. After calculating the crimes per mile, the Hot Spot analysis tool is run. The Hot Spot tool operates based on the null hypothesis of complete spatial randomness, and presents results that reject the null hypothesis and shows the crime patterns. The creation of the spatial weights matrix file for the scale of analysis and spatial autocorrelation of the data is compulsory before running the Hot Spot tool. The scale of analysis for this study includes only the intersecting streets, but it has the potential to include streets connected by drive time, walk time, or proximity, irrespective of the network connectivity. The spatial autocorrelation is performed using the Moran's I statistic to ensure the data shows randomness and clustering, as demonstrated by a high z-score. With high z-scores that reflect spatial clustering and a small p-value, the results are statistically significant and mean it is improbable (small probability) that the observed spatial pattern is the result of random processes. The small p-value rejects the null hypothesis from the Hot Spot tool, which states that there are noticeable clustering patterns in the data that the Hot Spot tool can display. Then using the crimes per mile, a Hot Spot analysis will be run on the linear network dataset, for each connecting street network, ensuring that the model only takes account of connecting streets to calculate the cluster statistics.

3.2. Data Selection and Sources

This section discusses various data needs required for the model to create Hot Streets. The data acquired includes data from government and public sector sources such as the Atlanta Police department, the Atlanta Regional Commission, and Open Street Map (OSM). Although there are other available sources for the listed datasets, it is essential that free data, which is readily available and accurate, be used to enable quick and reliable replicability of the model by any desired user. After the evaluation of the data for fitness of use for the current research, the author determined that only minor processing outside the ModelBuilder would be required. Table 1 below contains the datasets used to complete this thesis project, accompanied by the separate datatypes and descriptions; while Table 2 contains a list of software used for the entirety of this study.

Table 1. List of sources, and description of each required data.

Dataset	**File Type**	**Data Type**	**Source**	**Description and Attributes**	**Temporal Resolution of the Dataset**
Atlanta City Limits	Shapefile	Polygon Feature Class	Atlanta Regional Commission (ARC)	The downloaded shapefiles had the area and other polygon geometric attributes in the attribute table.	May 2018
Streets	Shapefile	Polyline Feature Class	Open Street Map	This shapefile provides a complete street shapefile than the initially downloaded 2017 TIGER line file.	May 2018

Dataset	**File Type**	**Data Type**	**Source**	**Description and Attributes**	**Temporal Resolution of the Dataset**
Crimes	Excel.xlxs	Point Feature Class	Atlanta Police Department	Data is updated monthly and is presented by Atlanta PD as an Excel sheet.	2017

Table 2. Summary of Required Software.

Software	**Manufacturer**	**Function**	**Access**
ArcGIS Pro	Esri	Hot Spot Analysis	USC GIST Server
Excel	Microsoft	View and edit crime data	Personal Laptop

3.2.1. Atlanta City Limit

The Atlanta city limit was used to set the boundaries needed to crop the streets shapefiles that fell entirely within the city. The data from the cities regional commission is essential as two counties currently fall within the boundary of the city.

3.2.1.1. Fitness for Use

The city boundary was fit for use since it accurately represented the city limits through all the associated counties. The shapefile was used to clip both the crimes dataset and streets data as the initial crime dataset had features that fell outside the city limits.

3.2.2. Streets

Streets provide the detailed level of analysis which creates Hot Streets, and this is the critical shapefile required for the model. The streets provide the primary routes of transportation for criminals to get to and away from locations, LEAs to patrol areas and respond to calls, and civilian's daily commute to and from their homes. A classification of different street types already performed on the streets dataset before it was download is accurate enough to eliminate further attribute table processing. Streets collected as shapefiles from the OSM website download as a vector polyline that is compatible with Esri products. The Atlanta city limits extends into two counties but not entirely, so some of the streets had to be cropped at the city boundary. The projected coordinate system (PCS) used for the final analysis was NAD_1983_UTM_Zone_16N.

There are eleven attributes for each street segment, notably the street names and street types/classes. The six important attributes for this analysis include 1) osm_id which is a unique ID for each linear feature; 2) code and 3) fclass which identify the different road classes, e.g., primary, secondary, tertiary, residential, service, and unclassified roads; 4) street names; 5) ref which contains the alternate state street names (e.g., street name West Hill Avenue is US84/US221/GA 38 in the ref column); and finally 6) Shape_length in meters.

3.2.2.1. Fitness for Use

The sole purpose of the streets is to spatially represent the crimes, as such the only criteria needed to determine the fitness of use in this study include spatial accuracy and street names already provided in the attribute table. The 2018 dataset provided by a credible source through OSM, has functional overlap with personally tested Orbview-3 satellite imagery downloaded from the United States Geological Survey (USGS) website. Other credible sources for this street dataset include the TIGER-Line Files from the U.S Census Bureau, which provided the base from which OSM created their road shapefiles. OSM streets are initially the 2005

TIGER line file from United States Census Bureau, with continual edits from the organization and volunteer contributions that are verified and approved.

3.2.2.2. Processing

The streets data went through some additional processing once in the model. The streets were clipped to only show those linear features within the city limits provided by ARC. The streets dataset was projected to NAD_1983_UTM_Zone_16N, which allowed streets geometry calculation for the provision of the length of each linear feature. The length is essential because it was used to determine the ratio of crimes per street, as longer street segments tend to have more crime. The streets with the added crime ratio were placed as inputs into the Hot Spot analysis tool to create the Hot Streets. Before running the tool, it is crucial to covert the null values within the Crimes per Mile (CPM) column to zeros (the rows remained null because when performing a crime per mile calculation, the streets with zero crime could not be divided to present a result). Within the Hot Spot tool, the conceptualization of spatial relationships is the spatial weight matrix file.

3.2.3. Crimes

Crime data was used to show where the offenses occurred along the streets. The crime data initially came in an excel sheet from the Atlanta police department and consisted of all the crimes that occurred in the year of 2017. The excel sheet contained the metadata explaining the different headings and crime types available for download on the police department website. The crimes were clipped using the Atlanta city limits boundary shapefile, as some police responses were to nearby cities. The data provided over 26,000 records, of which only ten rape accidents remained unused due to unavailable locations for privacy reasons. When displayed, the data showed clusters in downtown that were sufficient enough to be used to find clusters through Hot

Spot and Hot Streets. Crime attributes include the: MI_PRINX; offense_id; report date; occurrence date; Occurrence time; beat; location; MinOfucr and MinOfibr_code which contains numerical values that group the crimes types; Maximum number of victims; shifts; Average Day; UC2_Literal contains the crime type; neighborhood; X and Y locations. There are three shift types with two-hour overlaps for the city of Atlanta, they include the day (6am to 4pm), evening (2pm to 12am), and morning (10pm to 8am) shift.

3.2.3.1. Fitness for Use

The determining factor with regards to crime data fitness for use is the ability to integrate it within ArcGIS for quick automated spatial processing. The crimes already have latitude and longitude positions, which provide a means to integrate the data into the model quickly. The data is credible as the police department provides it, but there have been concerns about the spatial accuracy as to where the crimes were reported to occur when attached to the streets. Performing a random sampling of several crimes to nearest street connections provided a numeric value of accuracy to address the connection concerns in using personally non-geocoded data. A random sampling of the 26,318 crimes performed, at 95% confidence level with a 4% interval needs a sample size of 579. The random sampling shows that slightly over 81% of the data matched to the right streets, eliminating the need to geocode the dataset for this project. Most of the issues from the remaining 19% resulted from crimes at intersection points, or neighboring streets of buildings with two exits to both roads, which do not cause a significant impact in the data for this level of analysis because the analysis weighs connecting streets in the calculations. A Sergeant within the Tactical Crime Analysis Unit in the Atlanta PD provided assurances that the geocoded data by the police department is accurate since they place each point on the proper building/ edge of the road (Petersen, Robert E. Personal interview. 11 April 2018). The current data attributes as can be seen from Figure 3, which show the crime locations and streets names match nicely.

location	name
740 SIDNEY MARCUS BLVD NE	Sidney Marcus Boulevard Northeast
1080 HARDEE ST NE	Hardee Street Northeast
3257 W ROXBORO RD NE	Woods Circle Northeast
820 W MARIETTA ST NW	West Marietta Street Northwest
4 S EUGENIA PL NW	South Eugenia Place Northwest
63 LAKEVIEW DR NE	Lakeview Drive Northeast
2600 OLD HAPEVILLE RD SW	Old Hapeville Road Southwest
1500 WOODBINE AVE SE	Woodbine Avenue Southeast
1981 RENA CIR SW	Rena Circle Southwest
3857 ADAMSVILLE DR SW	Adamsville Drive Southwest
3990 N IVY RD NE	North Ivy Road Northeast
752 TERRY ST SE	Terry Street Southeast
1625 LORING DR NW	Loring Drive Northwest
3462 CREIGHTON RD SW	Creighton Road Southwest
1630 LAURELWOOD DR SW	Laurelwood Drive Southwest
740 SIDNEY MARCUS BLVD NE	Sidney Marcus Boulevard Northeast
1209 REDFORD DR SE	Redford Drive Southeast
965 SELLS AVE SW	Sells Avenue Southwest
1705 MARTIN L KING JR DR NW	Martin Luther King Jr Drive Southwest
1471 ALLEGHENY ST SW	Allegheny Street Southwest

Figure 3. Screenshot of crime locations (left) and the associated street names (right) from a random sampling across the full dataset

3.2.3.2. Processing

The crimes required pre-processing outside the model. They were given the same projection as the streets layer, then snapped to the closest roads. After the point snaps, each crime is associated with the closest street and summarized into the street layer table via a total count. The data went on to be processed on the street level to create Hot Streets. The crime point data is also an input for the Point Density tool and the Kernel Density tool, to compare the results of the model to current predominant crime analysis techniques. The Kernel Density tool calculates the density of features in a neighborhood around those features, while the point density tool calculates the density of point features around each output raster cell. Both density tools are used to create density crime reports.

3.3. GIS Procedures and Analysis Models

After gathering a general understanding of the appropriate approaches, a flowchart was developed to show the primary sequence of events (Figure 4). The simple flowchart can help users of other GIS software to see the needed steps quickly.

The flowchart from the research design in Figure 4 results in a different sequence of events due to the accumulation of tools grouped into different sections within the GIS ModelBuilder. Based on the model processing requirements, there will be seven main groups.

3.3.1. Select City Streets Excluding Expressways

The extraction of the needed street layer within the study area is the first step of the analysis, and will make the first group. Open street maps are usually downloaded for the entire state, using the city limits shapefile to clip the extents will provide the streets within the city limits alone. Following the creation of the street layer within the study area, is the removal of express lanes and exit ramps as highways are patrolled differently, and are not always connected to neighboring streets. Also, only a handful of crimes happened on them. Four tools were used in this process 1) Clip tool to create the Atlanta city streets, 2) the Make Feature Layer tool to create a layer that could be used by the 3) Select Layer by Attribute tool for inverse selection of expressways and exit ramps, and finally 4) the Copy Features tool that extracts the selected streets.

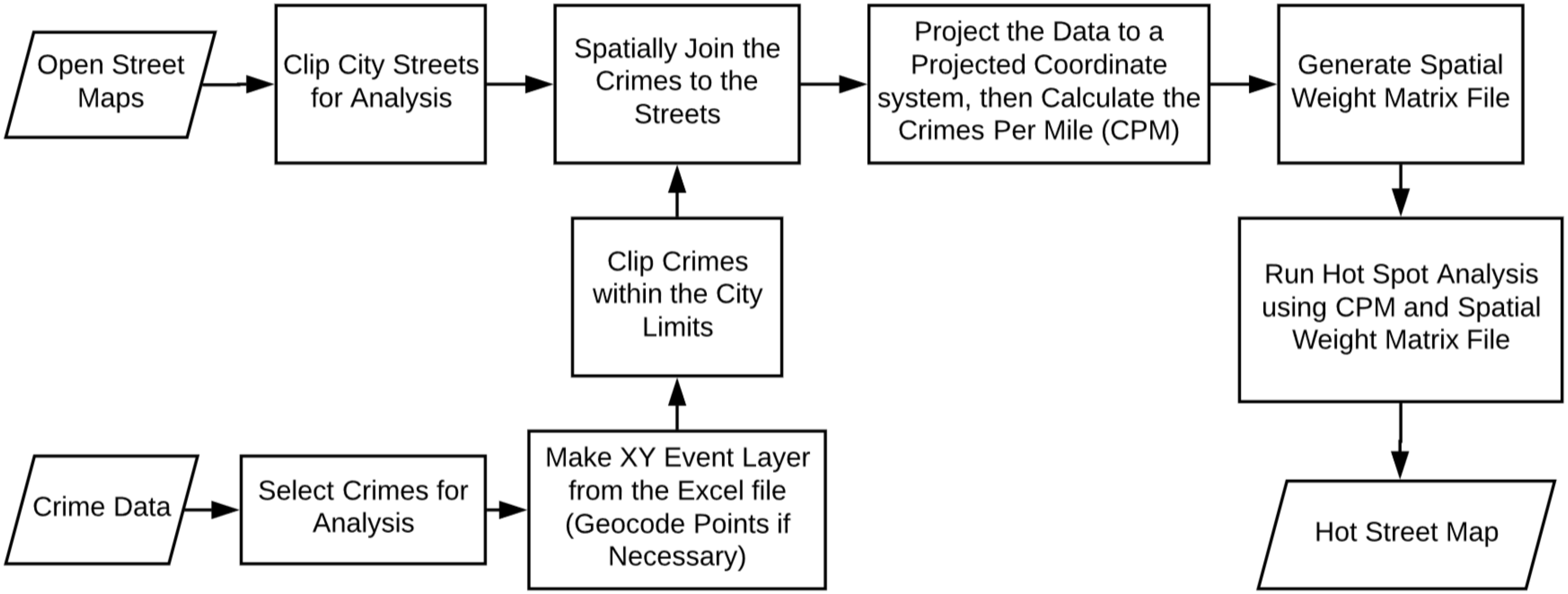


Figure 4. Flowchart of Hot Street Model

3.3.2. Select Crime Type and Shift

In tactical crime analysis situations, most of the analysis is performed in real time and for the purpose of briefing officers coming in at different shifts. Providing the option to analyze different crime types that occur during different shifts can help the incoming officers gain a better understanding of the current crime patterns and streets on which they occur. The two tools used within this group are the 1) Select Layer By Attribute which will show the expression as a parameter for different selection types, and the 2) Table Select tool used for the extracting the needed data for analysis.

3.3.3. Show Selected Crimes within the City

With the latitude and longitude information within the table, the point layers that fall within the city are developed. The data will not provide locations for rape, as there are no locations for privacy reasons. The two tools used in this grouped analysis are 1) Make XY Event Layer to create the shapefiles from the table, and 2) Clip tool for selecting only crimes within the city limits.

3.3.4. Spatial Join

This purpose of this grouped set of tools is the combination of the crime counts to the street layer. The same process was used by Dr. Lixin Huang (Esri, 2018b) in analyzing traffic accidents with 1) the Snap tool which joins the crimes to the nearest roads, and 2) the spatial join tool seen with the parameters in Figure 5.

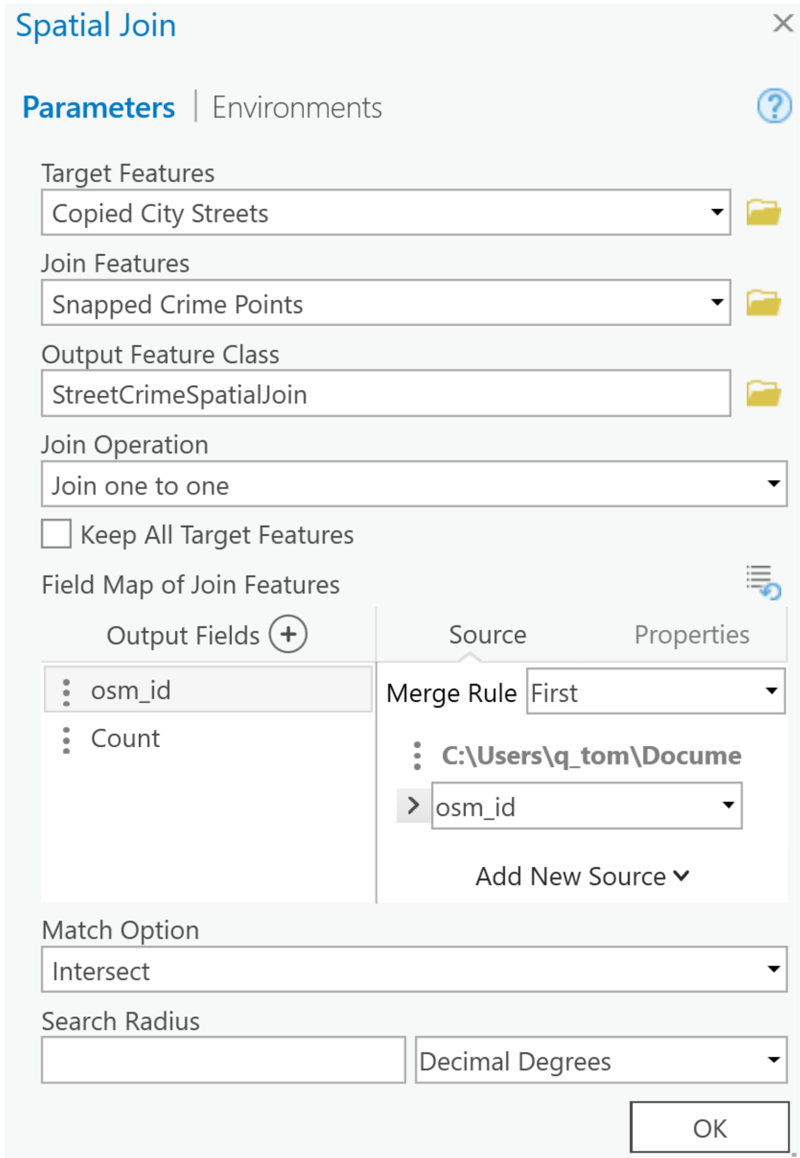


Figure 5. Screenshot of Spatial Join tool with inputs

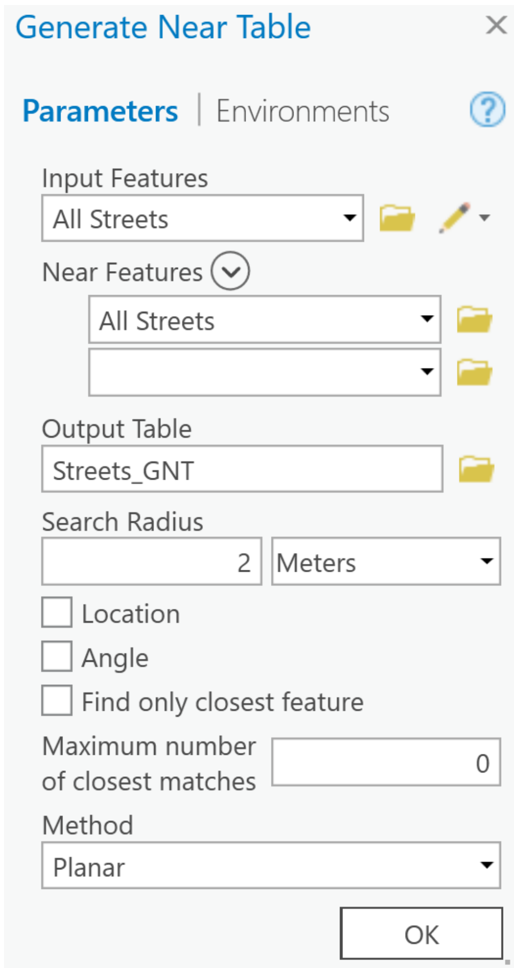
3.3.5. Project Streets and Calculate Crimes Per Mile (CPM)

The streets were also projected to display street lengths to be used to calculate the street crime count per length of each segment. The original street lengths provided with the street layer is no longer accurate because of the clipped road segments. The tools include 1) Project; 2) Add Field for the CPM column; 3) Calculate Field to divide the total snapped crimes by the segment lengths. The following section changes the NULLs into Zeros and reselects all layers otherwise the Generate Spatial Weight Matric File will not incorporate all the streets within the city streets.

3.3.6. Generate Spatial Weight Matrix (SWM) File

This portion of the model runs with seven different tools to generate the spatial weight matrix. Without this spatial weight matrix that tells the Hot Spot tool the neighboring features, the Hot Spot tool will select roads that do not intersect and may not have connectivity when looking at the street routes. The neighboring issue arises because the Hot Spot analysis tool is initially for only point and polygon layers.

The first performed function is the generation of a table with nearby streets by intersection with the Generate Near Table or the Summarize Nearby tool (Figure 6). The Summarize Nearby tool was tested but not used in the final model because of the 20 minute run time for this geoprocessing tool alone.



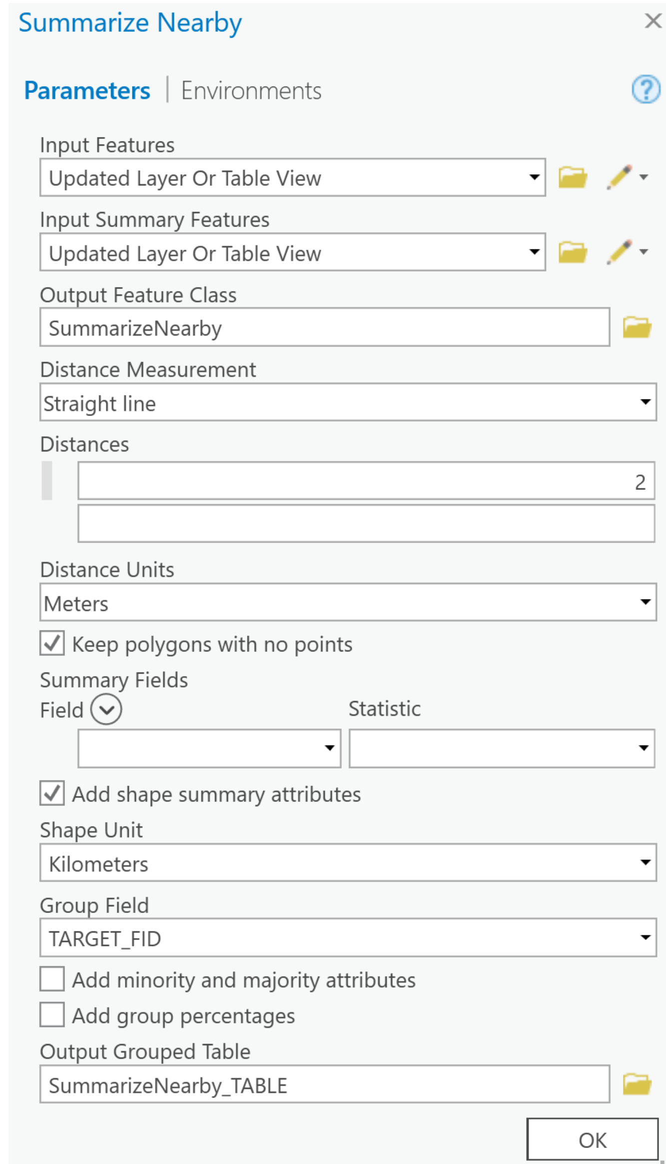


Figure 6. Screenshots of tools used to generate a near table for the SWM file

Next, the summarize Nearby tool creates the table, all distance types except straight-line distance use ArcGIS Online routing and network services. The distance measurement types include 1) Driving Distance; 2) Driving Time; 3) Straight Line; 4) Trucking Distance; 5) Trucking Time; 6) Walking Distance; 7) Walking Time. The distance types create polygons of buffers in a single table, which meet the required distance or drive time. The drive distance and time use the road network and obey all connectivity and speed limit rules. The drive-time and drive distance measurement options are not necessary for the development of this model but should others want to run drive-time, they must ensure that they have the appropriate license and credits.

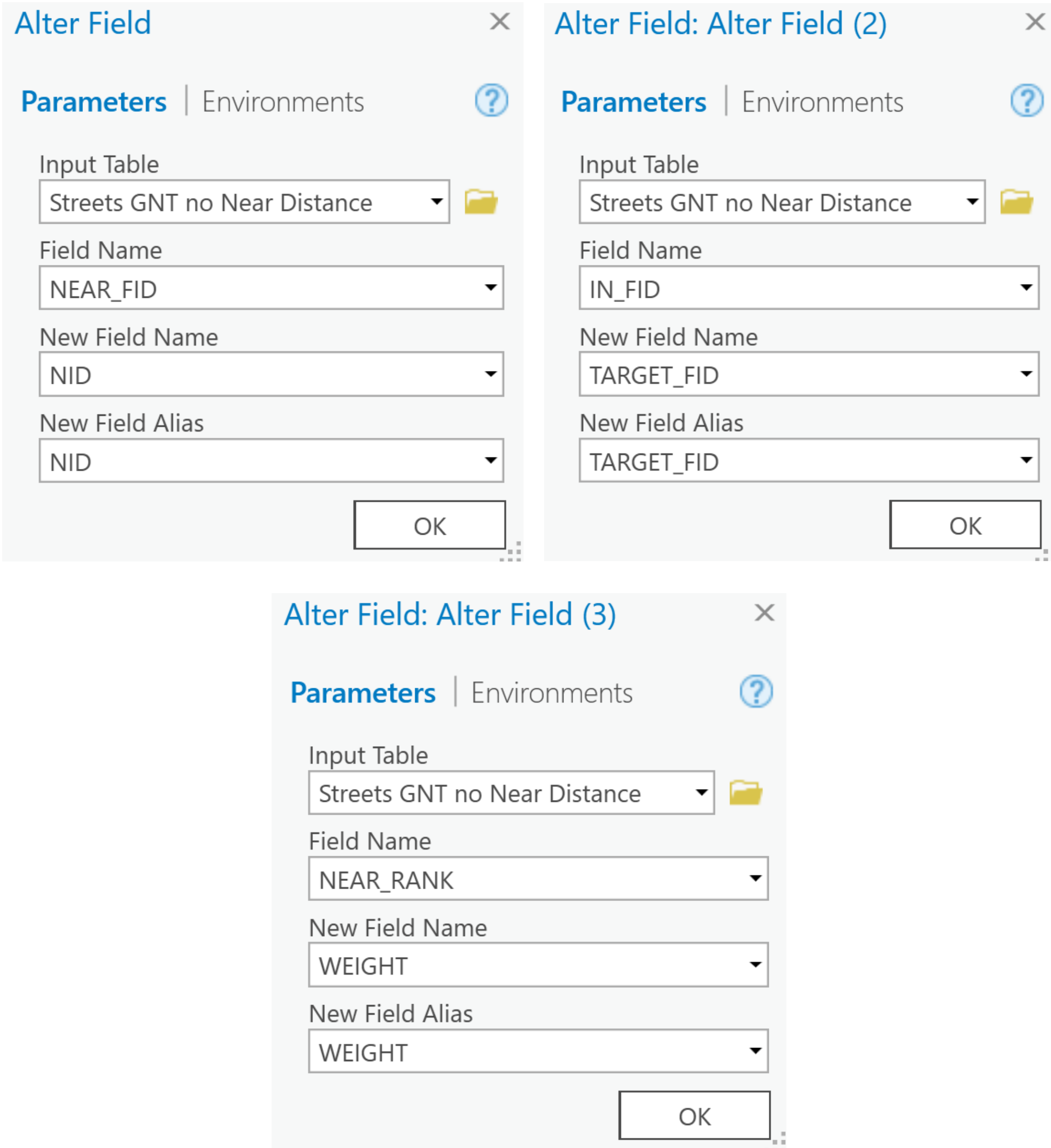


Figure 7. Altered fields after the generated nearby table.

After the table with the connected streets is created, the fields are altered (Figure 8) to meet the requirement for the Generate Spatial Weights Matrix tool. The tool requires three fields which include the OBJECTID; the UniqueID renamed as whatever unique numeric column for each row within the streets layer, the Near ID (NID) which holds the connected UniqueID values, and finally the WEIGHT. The created table is used to generate the .SWM file needed as an input table for Hot Spot Analysis tool as can be seen in Figure 8.

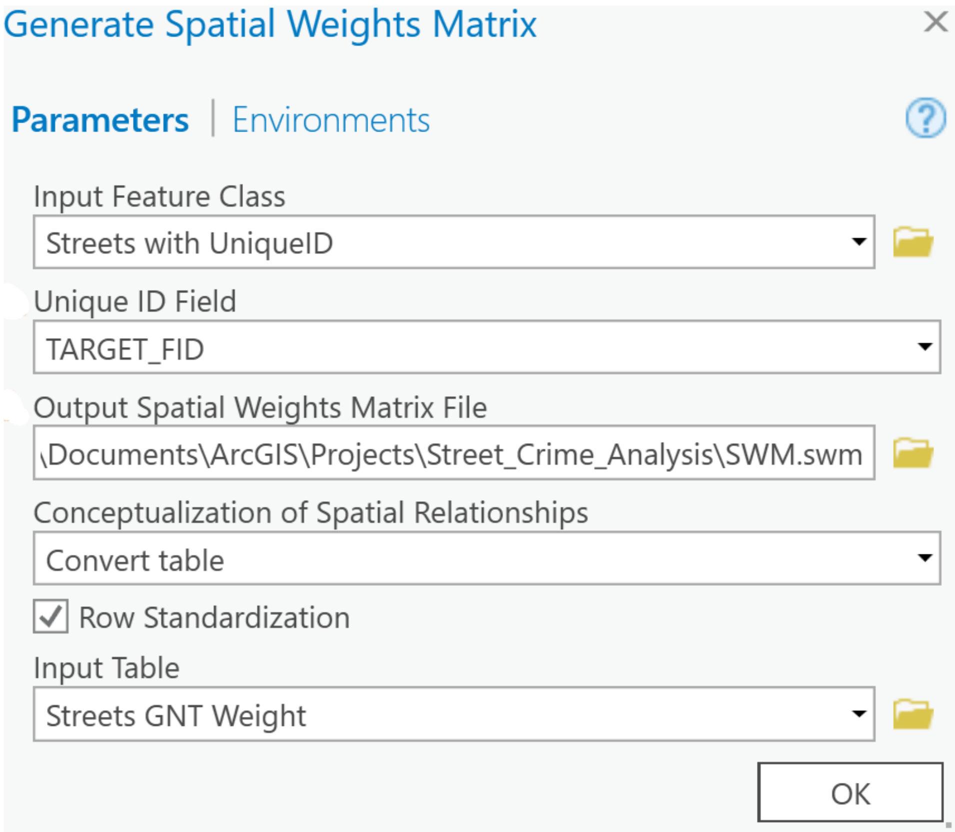


Figure 8. Generate Spatial Weights Matrix tool

3.3.7. Spatial Autocorrelation

The Moran's I statistic was performed before the Hot Spot tool to ensure there is perfect randomness in the data after given a set of weighted features. The Hot Spot tool (Figure 9) identifies statistically significant spatial clusters of high values (Hot Spots) and low values (Cold Spots) with the Getis-Ord Gi* statistic. It creates a new Output Feature Class with a z-score, p-value, number of neighbors, and confidence level bin (Gi_Bin) for each feature in the Input Feature Class.

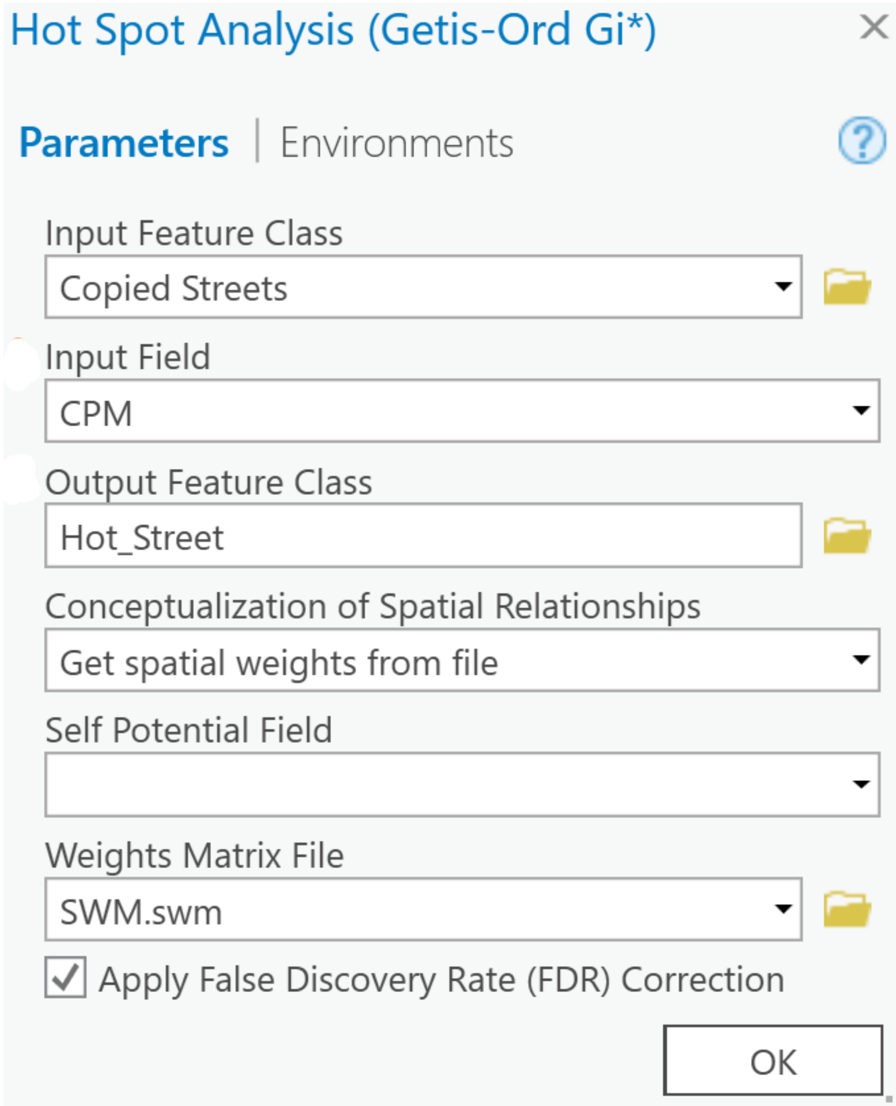


Figure 9. Hot Spot Analysis tool and parameters

3.4. Runs and Purpose

Several model runs selecting for different crime types and days/times were made to ensure the model ran smoothly. These use case examples are summarized in Table 3, along with the total run times for each model. As can be observed, the average runtime for the model is 5 minutes, and the number of crimes selected does not have much influence on the runtime. The reason these runs were selected is that criminology studies mostly use Part 1 crimes; crime studies on a street level use mostly auto-related crimes, and the remaining runs are to provide officers with a briefing of the developing crime patterns at the different shifts and weekdays.

Table 3: List of different runs, crime counts and run times.

Run	**Crime Count**	**Runtime**
Part 1 Crimes	26318	4 minutes 42 seconds
Auto Theft & Larceny From Vehicle	13010	4 minutes 2 seconds
Day Shift	6810	4 minutes 21 seconds
Evening Shift	9038	9 minutes 37 seconds
Morning Shift	6883	5 minutes 49 seconds
Weekdays	3449	3 minutes 41 seconds
Weekends	7176	3 minutes 50 seconds

Chapter 4 Results

Chapter 4 documents the results of the final Hot Street model. This chapter is broken into three sections to present the results of the analysis. Section 4.1 provides the Hot Street Model. Section 4.2 displays the results from the spatial autocorrelation. Section 4.3 displays the number of Hot Streets generated from each model run, with maps that display the locations in the city.

4.1. Hot Street Model

After performing several runs, the final model and parameters for the geoprocessing pane is finished and can be seen in Figures 10 and 11 with all the processing groups. There are a total number of 11 groups which execute different functions in the model, and nine parameters (see Appendix A for detailed sections of the Hot Street Model). The input parameters are displayed in a blue background for the layers, and white for the expression. The tools are displayed with a yellow background, while the outputs from the tools are shown with a green background. The first group consists of the model parameters and expression for the crime selection, which also appear in Figure 10. The other groups, as stated in the methodology, follow after the input parameters group and before the final result is displayed. Due to the number of tools used, setting preconditions is important for output results that are used as different tool inputs so that there will be a proper progression of analysis with no errors. After showing the created maps, the Hot Streets are hard to visually see since this level of analysis provides more specific results over larger geographic scales. The symbology is updated within the model to present statistically significant Hot Streets with thicker widths for quick identification.

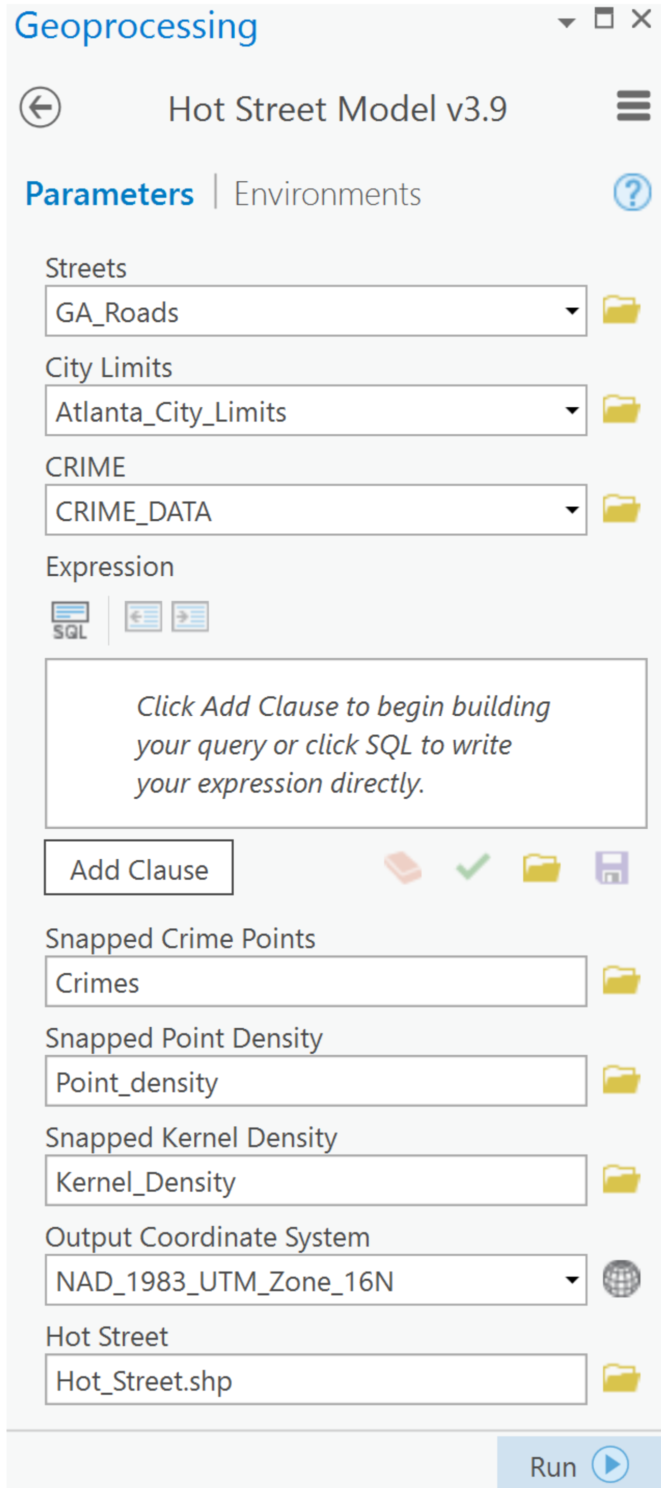


Figure 10. Hot Street Model as Geoprocessing Tool

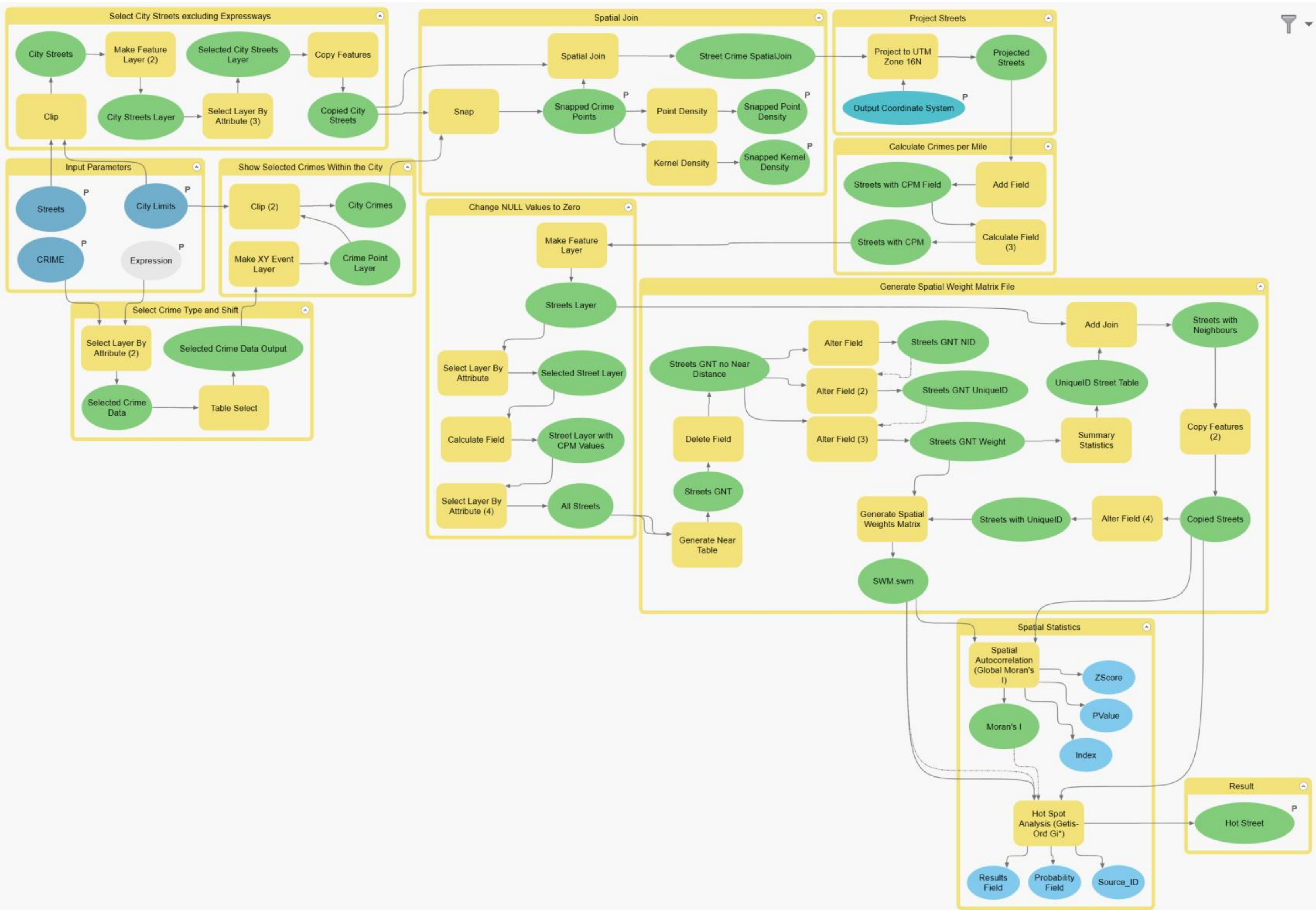


Figure 11. Hot Street Model

4.2. Spatial Autocorrelation

To ensure the spatial weight matrix contained a minimum of one neighbor is a scale of analysis with data that is randomly dispersed, the Moran's I tool is run before the Hot Spot Analysis. The Getis-Ord General G statistic is not used with the Gi* statistic because when the high and low values cluster, they cancel out (Esri 2018c). For this reason, the Moran's I spatial autocorrelation tool is used to measure the spatial clustering of where both the high values and low values cluster. Table 4 contains the results generated from the spatial autocorrelation tool. The high z-scores indicate there is clustering and less than 1% likelihood that the pattern is a result of random chance. The Moran's I values close to 0 indicate a pattern of perfect randomness.

Table 4. Moran's I Results

Run	**Z-Score**	**Moran's I**
Part 1 Crimes	8.767995	0.039697
Auto Theft & Larceny From Vehicle	7.238768	0.031967
Day Shift	7.729909	0.034891
Evening Shift	4.574907	0.030494
Morning Shift	16.784498	0.076841
Weekdays	8.795830	0.040214
Weekends	20.740992	0.094857

4.3. Hot Street Result

After creating the final model, all seven runs displayed different Hot Streets. The resultant Hot Streets are categorized into three different confidence levels at 90%, 95%, 99%. The different confidence levels are classified based on the z-scores and p-values. A 90% confidence level has a p-value < 0.10 and a z-score < -1.65 or $> +1.65$, a 95% confidence level has a p-value < 0.05 and a z-score < -1.96 or $> +1.96$, and the 99% confidence level has a p-value < 0.01 and a z-score < -2.58 or $> +2.58$. Table 5 shows the total number of Hot Streets generated from each model run for different street classes and CLs. Service roads had the highest number of Hot Streets for every run, followed by residential then tertiary or secondary roads.

Eight maps are created from the Hot Street model, the maps from the different runs can be seen from Figures 12 to 20. The Hot Street maps are placed over the kernel density results to show that the streets are mostly located in portions of the map that overlap with high density of crime. Each section with a map developed from the model contains two sections for the results. The first paragraph lists out the total number of Hot Streets at each confidence level (CL) for the different street classes. The second paragraph contains a total number of Hot Streets at different CL that overlaps with the different kernel density classes (generated using Jenks normal break classification).

Table 5. Number of Hot Streets generated from the model.

	Number of Hot Streets																		
Street Class	**Primary**			**Secondary**			**Tertiary**			**Residential**			**Service**			**Unclassified**			**Total**
CL (%)	90	95	99	90	95	99	90	95	99	90	95	99	90	95	99	90	95	99	
Part 1 Crimes	_	_	1	4	2	6	_	2	6	4	7	19	26	56	280	_	_	_	413
Auto Theft & Larceny From Vehicle	_	1	_	_	1	5	1	1	4	2	7	15	26	41	218	_	_	_	322
Day Shift	_	_	1	2	4	4	_	_	6	1	3	16	30	41	225	_	_	_	333
Evening Shift	_	1	_	3	2	5	_	1	6	1	3	10	40	37	264	_	_	_	373
Morning Shift	_	_	3	2	3	5	_	3	3	8	3	20	23	47	242	_	1	2	365
Weekdays	_	_	_	5	1	6	1	1	6	3	2	18	28	71	325	_	_	_	467
Weekends	_	_	2	2	4	5	_	1	2	3	5	29	37	59	275	_	_	1	425

4.3.1. Part I

Part I crimes have a total number of 413 Hot Streets appearing on five street classes (refer to Figure 12). For the service class, a total of 362 streets are displayed high crime clusters for all CLs combined. There are 280 streets at 99% CL, 56 streets at 95% CL, and 26 streets at 90% CL. The residential class has a total of 30 streets that display high crime clusters for all CLs combined. There are 19 streets at 99% CL, 7 streets at 95% CL, and 4 streets at 90% CL. The secondary class has a total of 12 streets that display high crime clusters for all CLs combined. There are 6 streets at 99% CL, 2 streets at 95% CL, and 4 streets at 90% CL. The tertiary class has a total of 8 streets that display high crime clusters for all CLs combined. There are 6 streets at 99% CL, 2 streets at 95% CL, and none represented at the 90% CL. The primary class is the last class with only one street at the 99% CL.

Enlarged zoomed SW grid from Figure 12 can be seen in Figure 13. The purpose of Figure 13 is to make it easier to see the Hot Streets and overlap. The map on the far left shows the Hot Spot grids, the map in the middle shows the kernel density and Hot Streets, and the map on the right shows only the Hot Streets. As can be seen from Figure 13, there is also a good overlap between the Hot Spots and the Hot Streets.

Using the Kernel Density data, there are six classes generated from natural breaks. Class one to six going from the lowest (<= 0.26) to highest densities (<= 7.34) have a different number of streets that have their centers in them. On the lowest class of the kernel density, 2 Hot Streets are found at the 99% CL. The second class has 21 Hot Streets that fall within the grids; 18 Hot Streets from the 99% CL, 2 from the 95% CL, and 1 street from the 90% CL. The third class has a total of 124 Hot Streets; 93 Hot Streets from the 99% CL, 23 from the 95% CL, 8 from the 90% CL. The fourth class has 95 Hot Streets; 66 from the 99% CL, 20 from the 95% CL, 9 from the 90% CL. The fifth class has 126 streets; 96 from the 99% CL, 21 from the 95% CL, 9 from the 90% CL. The sixth class has 50 streets; 40 from the 99% CL, 2 from the 95% CL, 8 from the 90% CL.

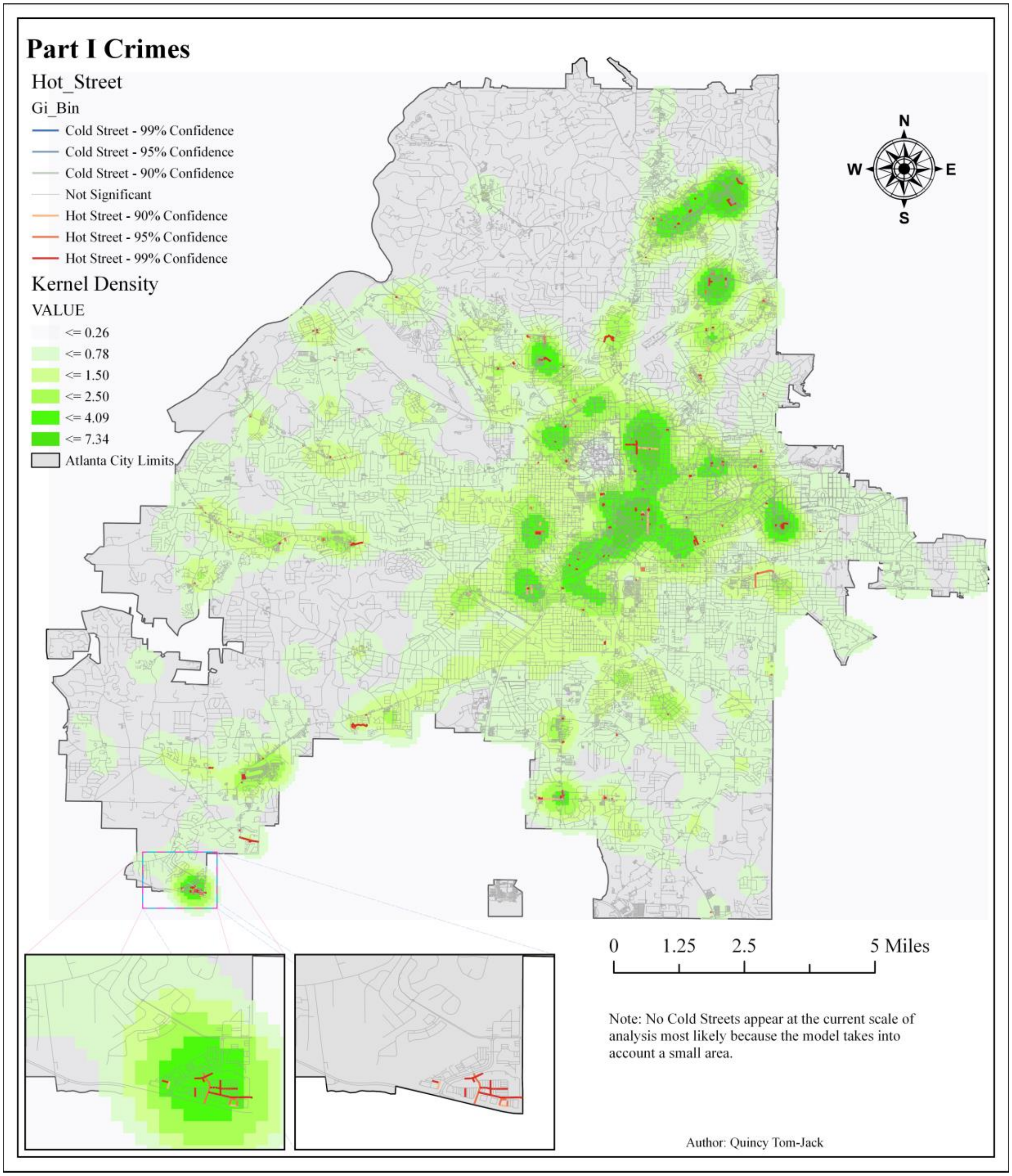


Figure 12. Hot Street map of Part I crimes

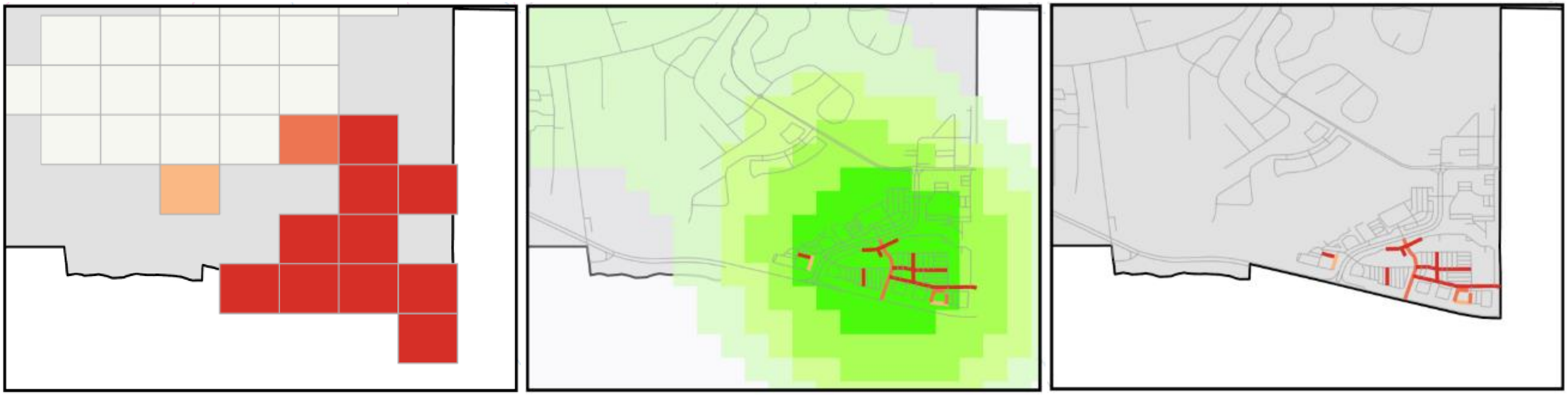


Figure 13. Zoomed in SW section of the Part I Hot Street Map

4.3.2. Auto Theft

Auto theft and vehicle larceny crimes have a total of 322 Hot Streets appearing on five street classes (Figure 14). For the service class, a total of 285 streets are displayed high crime clusters for all CLs combined. There are 218 streets at 99% CL, 41 streets at 95% CL, and 26 streets at 90% CL. The residential class has a total of 24 streets that display high crime clusters for all CLs combined. There are 15 streets at 99% CL, 7 streets at 95% CL, and 2 streets at 90% CL. The secondary class has a total of 6 streets that display high crime clusters for all CLs combined. There are 5 streets at 99% CL, 1 streets at 95% CL, and no streets at 90% CL. The tertiary class has a total of 6 streets that display high crime clusters for all CLs combined. There are 4 streets at 99% CL, 1 streets at 95% CL, and 1 street represented at the 90% CL. The primary class is the last class with only one street at the 95% CL.

Using the Kernel Density Data, there are six classes generated from a natural breaks. Class one to six going from the lowest (<= 0.11) to highest (<= 3.55) densities. On the lowest class of the kernel density, no Hot Streets are found. The second class has 21 Hot Streets that fall within the grids; 19 Hot Streets from the 99% CL, 1 from the 95% CL, and 1 street from the 90% CL. The third class has a total of 66 Hot Streets; 50 Hot Streets from the 99% CL, 12 from the 95% CL, 4 from the 90% CL. The fourth class has 91 Hot Streets; 61 from the 99% CL, 20 from the 95% CL, 10 from the 90% CL. The fifth class has 104 streets; 80 from the 99% CL, 14 from the 95% CL, 10 from the 90% CL. The sixth class has 44 streets; 35 from the 99% CL, 4 from the 95% CL, 5 from the 90% CL.

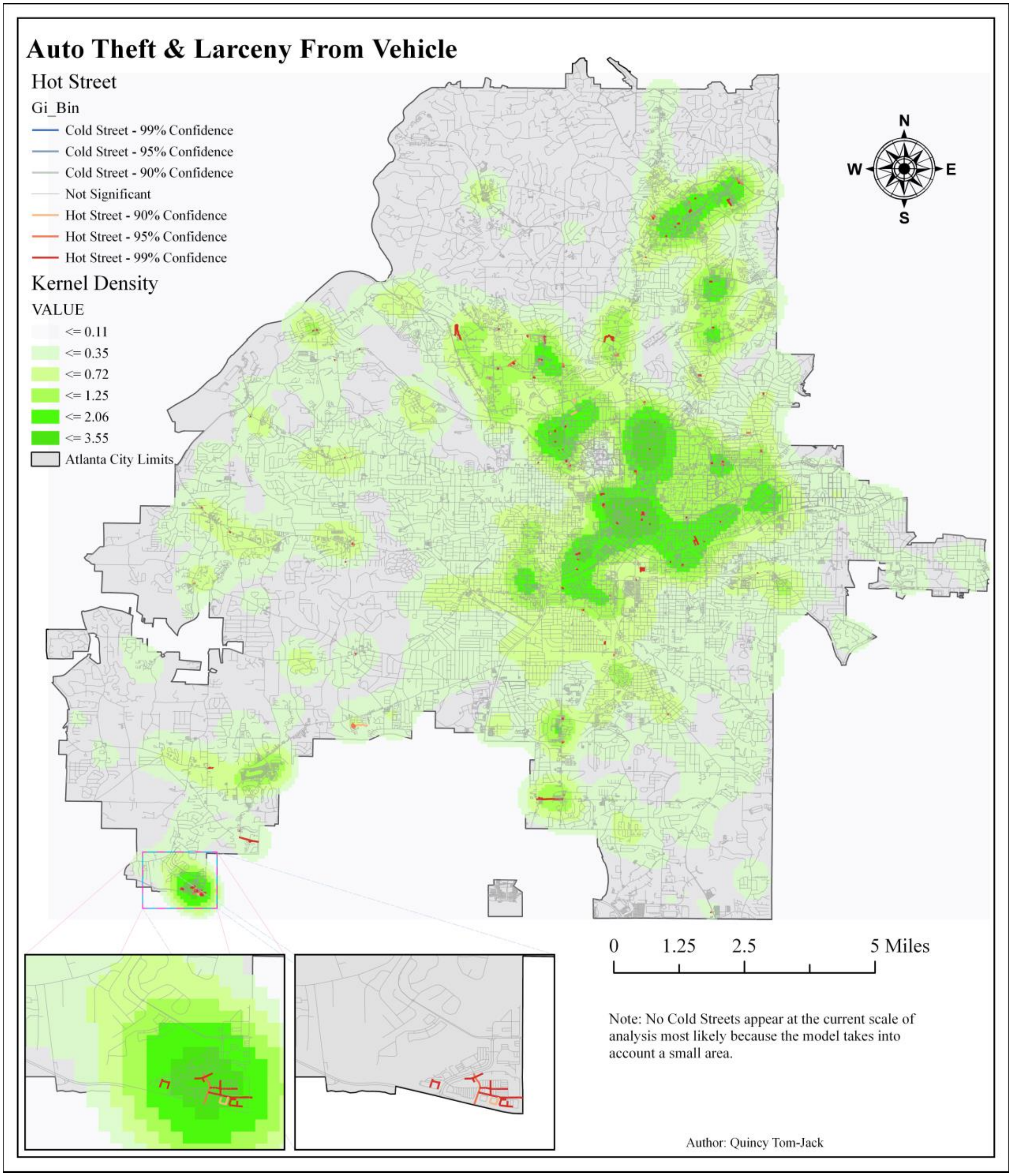


Figure 14. Hot Street map of Auto Theft and Vehicle Larceny

4.3.3. Day Shift

Day shift crimes have a total of 333 Hot Streets appearing on five street classes (Figure 15). For the service class, a total of 296 streets are displayed high crime clusters for all CLs combined. There are 225 streets at 99% CL, 41 streets at 95% CL, and 30 streets at 90% CL. The residential class has a total of 20 streets that display high crime clusters for all CLs combined. There are 16 streets at 99% CL, 3 streets at 95% CL, and 1 streets at 90% CL. The secondary class has a total of 10 streets that display high crime clusters for all CLs combined. There are 4 streets at 99% CL, 4 streets at 95% CL, and 2 streets at 90% CL. The tertiary class has a total of 6 streets that display high crime clusters at 99% CL. The primary class is the last class with only 1 street at the 99% CL.

Using the Kernel Density Data, there are six classes generated from a normal density. Class one to six going from the lowest (<=0.06) to highest (<=1.59) densities. On the lowest class of the kernel density, no Hot Streets are found. The second class has 28 Hot Streets that fall within the grids; 24 Hot Streets from the 99% CL, 2 from the 95% CL, and 2 street from the 90% CL. The third class has a total of 93 Hot Streets; 68 Hot Streets from the 99% CL, 11 from the 95% CL, 14 from the 90% CL. The fourth class has 94 Hot Streets; 69 from the 99% CL, 16 from the 95% CL, 9 from the 90% CL. The fifth class has 72 streets; 52 from the 99% CL, 15 from the 95% CL, 5 from the 90% CL. The sixth class has 51 streets; 43 from the 99% CL, 5 from the 95% CL, 3 from the 90% CL.

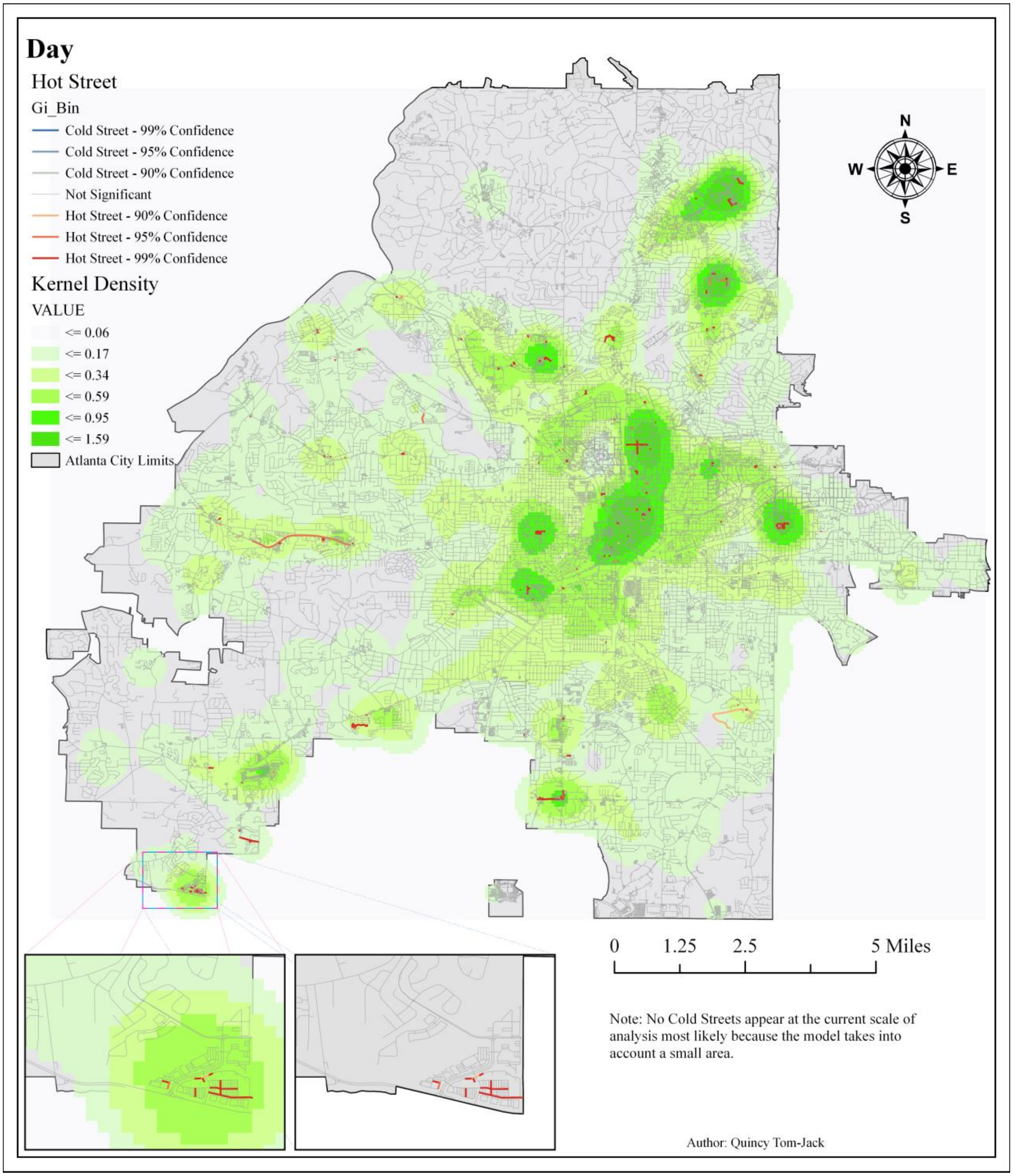


Figure 15. Hot Street map of crimes that occurred during the day shift

4.3.4. Evening Shift

Evening shift crimes have a total of 373 Hot Streets appearing on five street classes (Figure 16). For the service class, a total of 341 streets are displayed high crime clusters for all CLs combined. There are 264 streets at 99% CL, 37 streets at 95% CL, and 40 streets at 90% CL. The residential class has a total of 13 streets that display high crime clusters for all CLs combined. There are 10 streets at 99% CL, 3 streets at 95% CL, and 1 streets at 90% CL. The secondary class has a total of 10 streets that display high crime clusters for all CLs combined. There are 5 streets at 99% CL, 2 streets at 95% CL, and 3 streets at 90% CL. The tertiary class has a total of 7 streets that display high crime clusters for all CLs combined. There are 6 streets at 99% CL, 1 streets at 95% CL, and no street represented at the 90% CL. The primary class is the last class with only one street at the 95% CL.

Using the Kernel Density Data, there are six classes generated from a normal density. Class one to six going from the lowest (<= 0.09) to highest (<= 3.34) densities. On the lowest class of the kernel density, one Hot Street at 99% CL is found. The second class has 41 Hot Streets that fall within the grids; 31 Hot Streets from the 99% CL, 9 from the 95% CL, and 1 street from the 90% CL. The third class has a total of 121 Hot Streets; 92 Hot Streets from the 99% CL, 18 from the 95% CL, 11 from the 90% CL. The fourth class has 90 Hot Streets; 75 from the 99% CL, 2 from the 95% CL, 13 from the 90% CL. The fifth class has 119 streets; 85 from the 99% CL, 15 from the 95% CL, 19 from the 90% CL. The sixth class has 4 streets from the 99% CL.

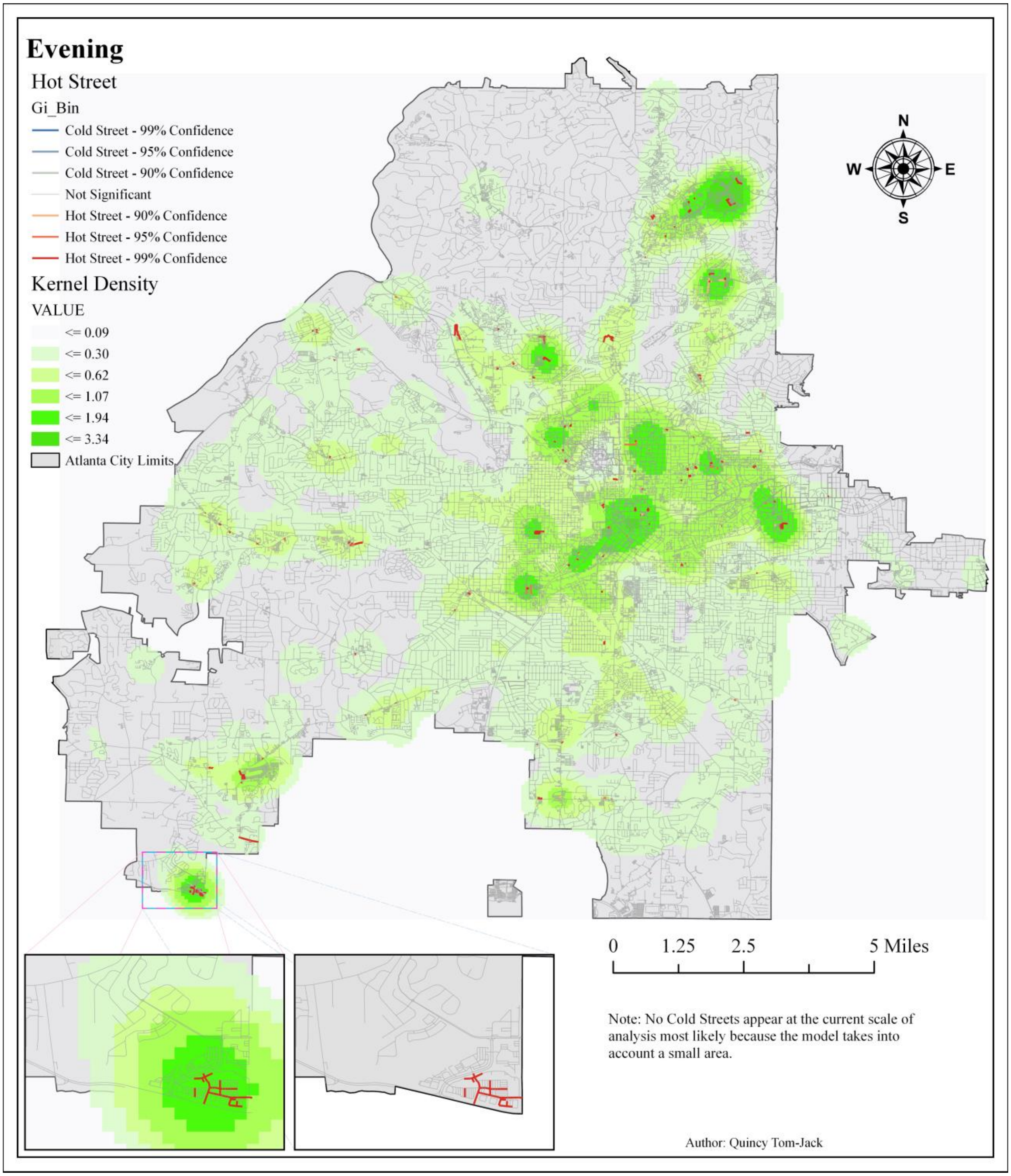


Figure 16. Hot Street map of crimes that occurred during the evening shift

4.3.5. Morning Shift

Morning shift crimes have a total of 365 Hot Streets appearing on five street classes (Figure 17). For the service class, a total of 312 streets are displayed high crime clusters for all CLs combined. There are 242 streets at 99% CL, 47 streets at 95% CL, and 23 streets at 90% CL. The residential class has a total of 31 streets that display high crime clusters for all CLs combined. There are 20 streets at 99% CL, 3 streets at 95% CL, and 8 streets at 90% CL. The secondary class has a total of 10 streets that display high crime clusters for all CLs combined. There are 5 streets at 99% CL, 3 streets at 95% CL, and 2 streets at 90% CL. The tertiary class has a total of 6 streets that display high crime clusters for all CLs combined. There are 3 streets at 99% CL, 3 streets at 95% CL, and no street represented at the 90% CL. The primary with 3 streets at the 99% CL, and the Unclassified class with 3 total streets of which 2 are at 99% CL and 1 street at 95% CL.

Using the Kernel Density Data, there are six classes generated from a normal density. Class one to six going from the lowest (<= 0.06) to highest (<=1.36) densities. On the lowest class of the kernel density, 2 Hot Streets are found, 1 for both the 99% and 95% CL. The second class has 35 Hot Streets that fall within the grids; 24 Hot Streets from the 99% CL, 7 from the 95% CL, and 4 street from the 90% CL. The third class has a total of 93 Hot Streets; 71 Hot Streets from the 99% CL, 14 from the 95% CL, 8 from the 90% CL. The fourth class has 110 Hot Streets; 86 from the 99% CL, 15 from the 95% CL, 9 from the 90% CL. The fifth class has 56 streets; 42 from the 99% CL, 11 from the 95% CL, 3 from the 90% CL. The sixth class has 73 streets; 53 from the 99% CL, 11 from the 95% CL, 9 from the 90% CL.

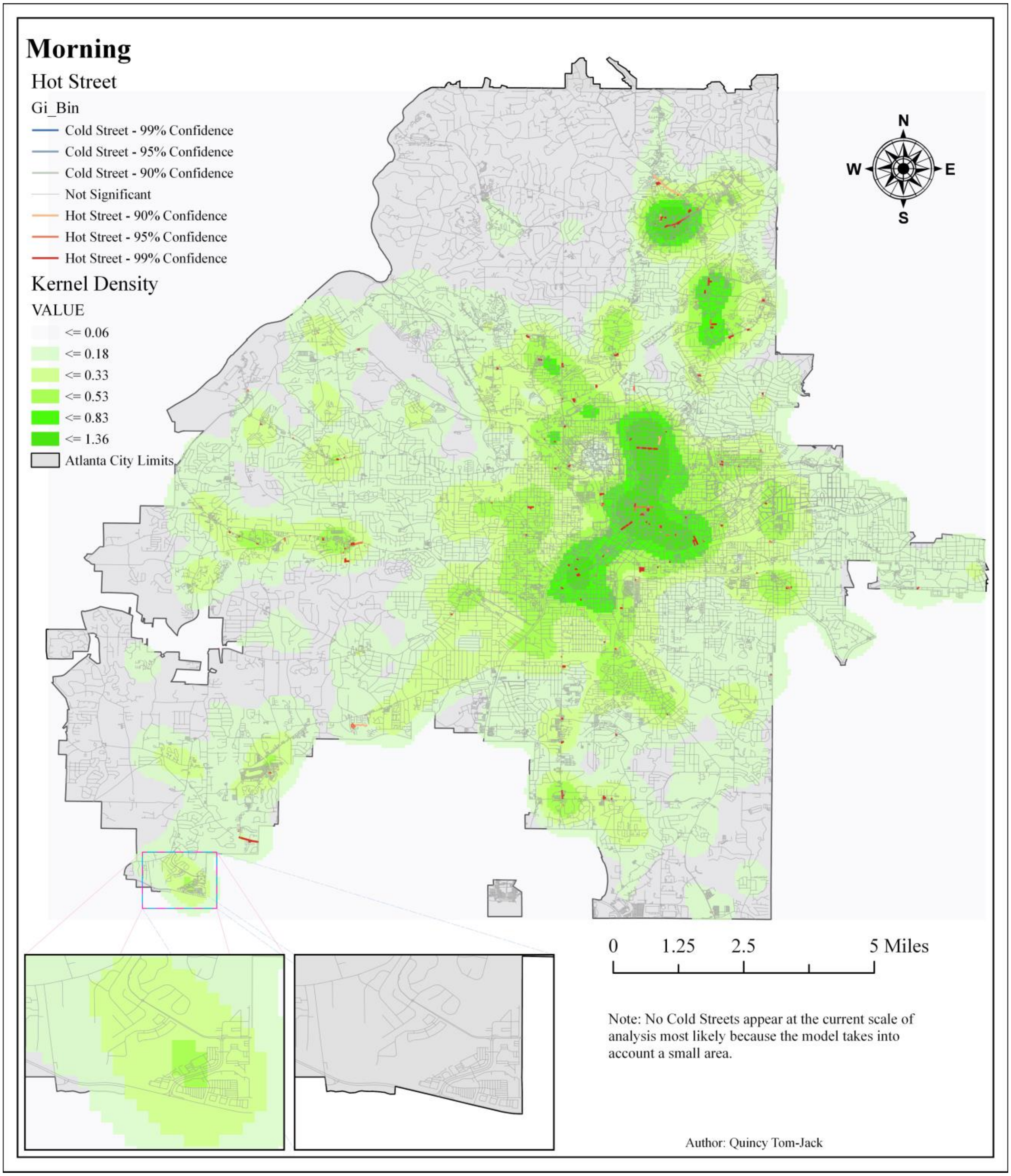


Figure 17. Hot Street map of crimes that occurred during the morning shift

4.3.6. Weekday

Weekday crimes have a total of 467 Hot Streets appearing on four street classes (Figure 18). For the service class, a total of 424 streets are displayed high crime clusters for all CLs combined. There are 325 streets at 99% CL, 71 streets at 95% CL, and 28 streets at 90% CL. The residential class has a total of 23 streets that display high crime clusters for all CLs combined. There are 18 streets at 99% CL, 2 streets at 95% CL, and 3 streets at 90% CL. The secondary class has a total of 12 streets that display high crime clusters for all CLs combined. There are 6 streets at 99% CL, 1 street at 95% CL, and 5 streets at 90% CL. The tertiary class has a total of 8 streets that display high crime clusters for all CLs combined. There are 6 streets at 99% CL, 1 street at 95% CL, and 1 street represented at the 90% CL.

Using the Kernel Density Data, there are six classes generated from a normal density. Class one to six going from the lowest (<= 0.03) to highest (<= 0.67) densities. On the lowest class of the kernel density, 4 Hot Streets are found; 2 streets are found with 99% CL, 1 streets with both the 95% and 90% CL. The second class has 32 Hot Streets that fall within the grids; 26 Hot Streets from the 99% CL, 6 from the 95% CL. The third class has a total of 127 Hot Streets; 91 Hot Streets from the 99% CL, 21 from the 95% CL, 15 from the 90% CL. The fourth class has 127 Hot Streets; 98 from the 99% CL, 18 from the 95% CL, 11 from the 90% CL. The fifth class has 118 streets; 91 from the 99% CL, 22 from the 95% CL, 5 from the 90% CL. The sixth class has 69 streets; 53 from the 99% CL, 9 from the 95% CL, 7 from the 90% CL.

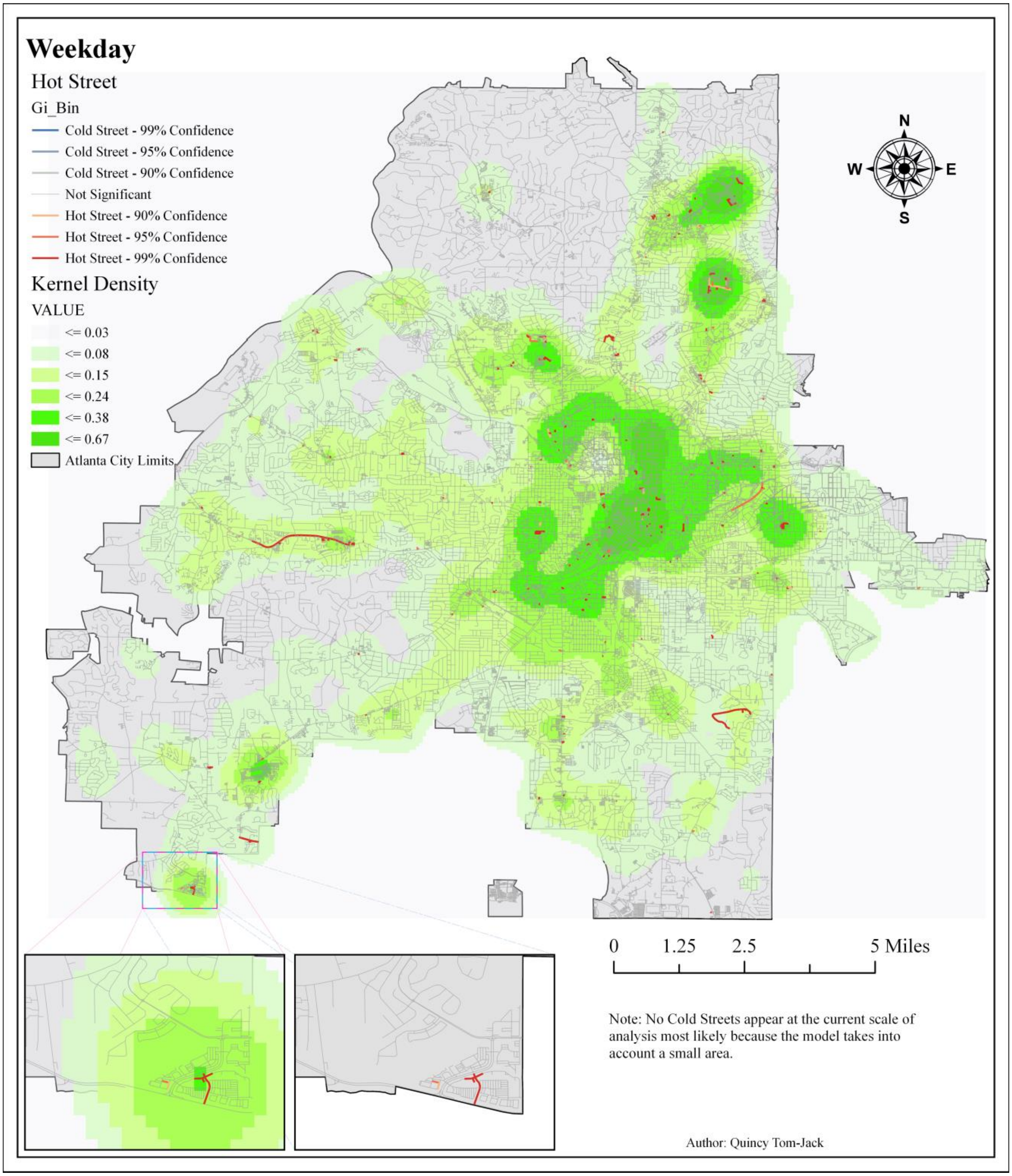


Figure 18. Hot Street map of weekday crimes

4.3.7. Weekend

Weekend crimes have a total of 425 Hot Streets appearing on five street classes (Figure 19). For the service class, a total of 371 streets are displayed high crime clusters for all CLs combined. There are 275 streets at 99% CL, 59 streets at 95% CL, and 37 streets at 90% CL. The residential class has a total of 37 streets that display high crime clusters for all CLs combined. There are 29 streets at 99% CL, 5 streets at 95% CL, and 3 streets at 90% CL. The secondary class has a total of 11 streets that display high crime clusters for all CLs combined. There are 5 streets at 99% CL, 4 streets at 95% CL, and 2 streets at 90% CL. The tertiary class has a total of 3 streets that display high crime clusters for all CLs combined. There are 2 streets at 99% CL, 1 streets at 95% CL, and no street represented at the 90% CL. The primary class is the last class with only 2 streets at the 99% CL.

Using the Kernel Density Data, there are six classes generated from a normal density. Class one to six going from the lowest (<= 0.07) to highest (<= 1.69) densities. On the lowest class of the kernel density, 4 Hot Streets are found; 2 at the 99% and 90% CL. The second class has 42 Hot Streets that fall within the grids; 32 Hot Streets from the 99% CL, 8 from the 95% CL, and 2 street from the 90% CL. The third class has a total of 113 Hot Streets; 86 Hot Streets from the 99% CL, 11 from the 95% CL, 16 from the 90% CL. The fourth class has 116 Hot Streets; 84 from the 99% CL, 25 from the 95% CL, 7 from the 90% CL. The fifth class has 121 streets; 91 from the 99% CL, 17 from the 95% CL, 13 from the 90% CL. The sixth class has 33 streets; 22 from the 99% CL, 8 from the 95% CL, 3 from the 90% CL.

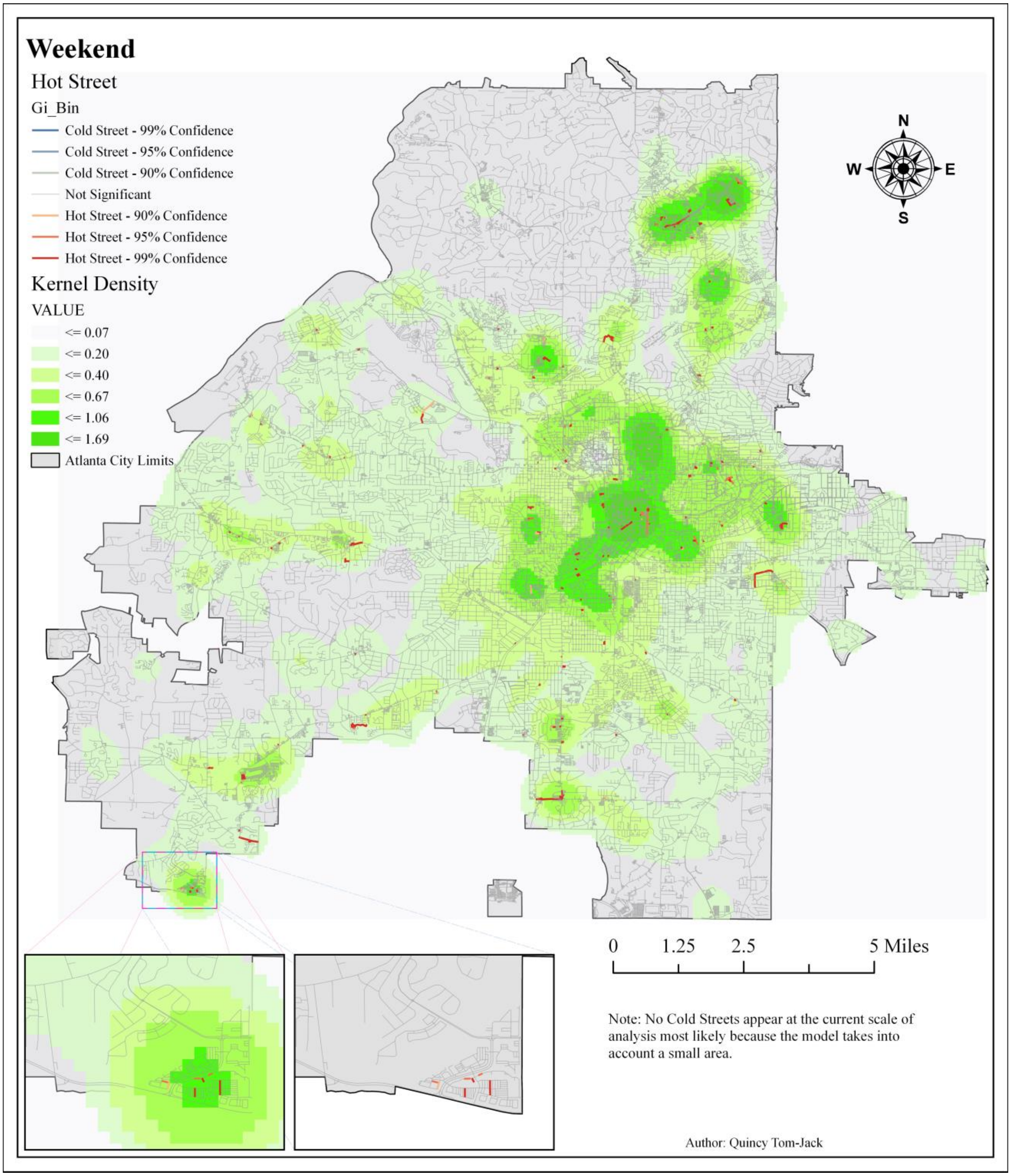


Figure 19. Hot Street map of weekend crimes

4.3.8. Part I Houston, Texas.

An additional run was performed to test the models ability to run in different cities. Houston, Texas was chosen because of the available data provided by the City of Houston for all model parameters. The crime data ranges from July, 2018 to August 20, 2018. Houston Part I crimes have a total of 910 Hot Streets appearing on five street classes (Figure 20). For the service class, a total of 153 streets are displayed high crime clusters for all CLs combined. There are 134 streets at 99% CL, 14 streets at 95% CL, and 5 streets at 90% CL. The residential class has a total of 76 streets that display high crime clusters for all CLs combined. There are 61 streets at 99% CL, 10 streets at 95% CL, and 5 streets at 90% CL. The secondary class has a total of 460 streets that display high crime clusters for all CLs combined. There are 385 streets at 99% CL, 51 streets at 95% CL, and 24 streets at 90% CL. The tertiary class has a total of 83 streets that display high crime clusters for all CLs combined. There are 67 streets at 99% CL, 9 streets at 95% CL, and 7 at the 90% CL. The primary class has a total of 125 streets. There are 105 streets at the 99% CL, 14 streets at the 95% CL, and 6 streets at the 90% CL. There are 13 unclassified Hot Streets. 11 of which fall into the 99% CL, and 1 in both the 95% and 90% CL.

Using the Kernel Density Data, there are six classes generated from a normal density. Class one to six going from the lowest (<= 0.09) to highest (<= 3.39) densities. On the lowest class of the kernel density, 13 Hot Streets are found in total; 8 at the 99% CL, 3 at the 95% CL, 2 at the 90% CL. The second class has 80 Hot Streets that fall within the grids; 64 Hot Streets from the 99% CL, 8 from the 95% CL, and 8 street from the 90% CL. The third class has a total of 325 Hot Streets; 282 Hot Streets from the 99% CL, 28 from the 95% CL, 15 from the 90% CL. The fourth class has 340 Hot Streets; 280 from the 99% CL, 39 from the 95% CL, 21 from the 90% CL. The fifth class has 186 streets; 165 from the 99% CL, 16 from the 95% CL, 5 from the 90% CL. The sixth class has 63 streets; 47 from the 99% CL, 13 from the 95% CL, 3 from the 90% CL.

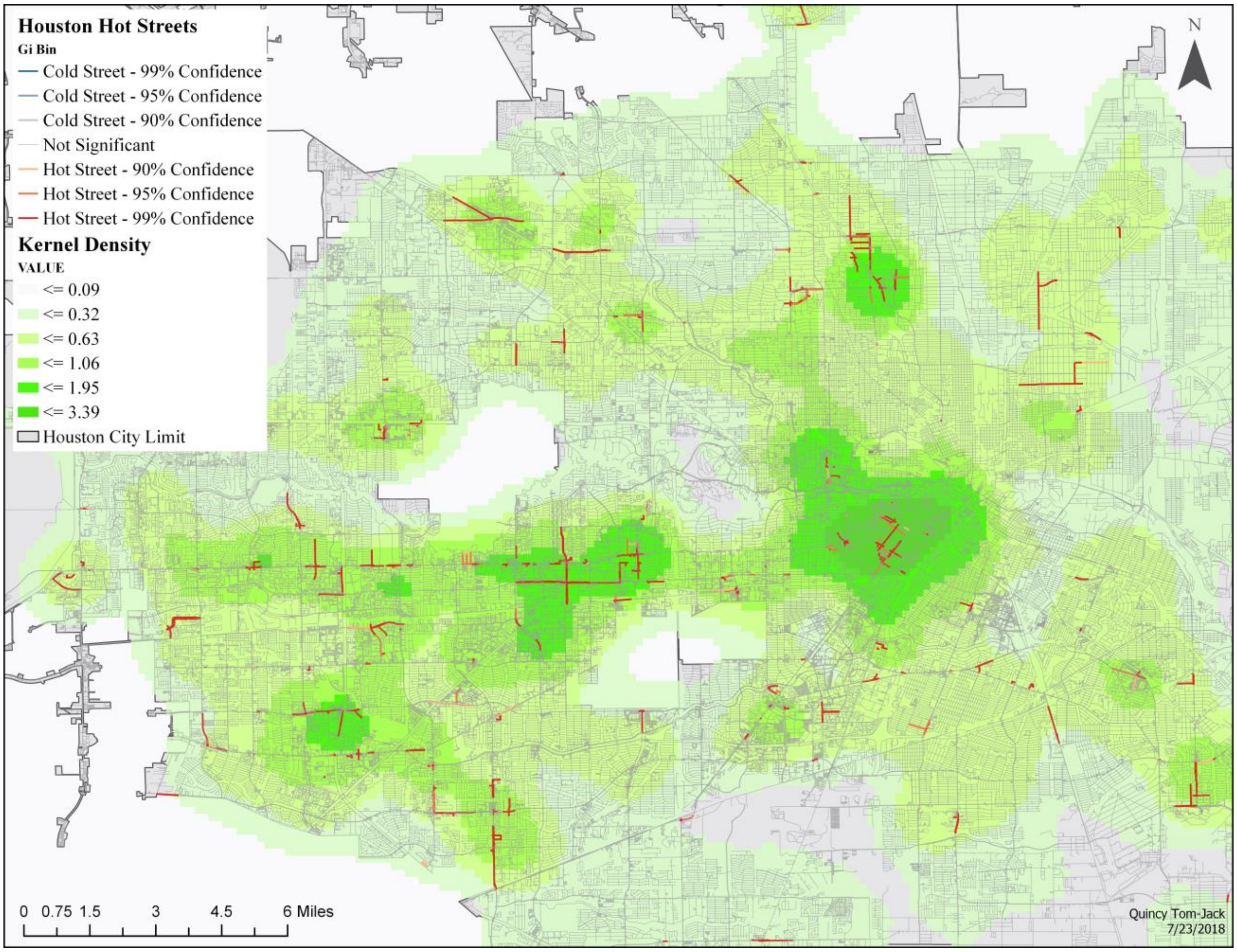


Figure 20. Part I Hot Street of Central Houston, Texas

Chapter 5 Discussion and Conclusions

The model is successful in providing an effective way to depict Hot Streets, despite all the challenges faced. This chapter discusses the key findings and possible impact of the findings, as well as the research limitations and future research.

5.1. Findings and Impact

5.1.1. Model

Through the course of developing this model, it was discovered that the model could easily be replicated for different scales that utilize street attributes to change the number of influencing street segments. After the first run, the model time can be improved by removing some of the tools that would provide the same output despite the change in crime selection. The removal of some of the grouped processes and tools can be adjusted to suit the efficient needs of the analyst or researcher if the study is performed over the same area on multiple runs. After the first run, the first group that can be removed is the Select City Streets group if the study area remains the same. With the same study area, there is no need to create the same street layer for snapping features continuously. The second group that can be changed is the Generate Spatial Weight Matrix File group. Within the group, the spatial weight matrix input table is created with the first five tools. The table can remain the same if the output street layer at the end of the Select City Streets remains unchanged, and the scale of analysis is the same. This is because the street ID is used to distinguish each linear feature and the streets included for the spatial statistics.

The model takes a considerable amount of time to run, the average time of the model when using the Generate Near Table tool to create the spatial weight matrix input table is 5 minutes. If the Summarize Nearby tool is used to create the spatial weight input table, the runtime for the same scale of analysis will be increased by approximately 25 minutes, to bring the full model runtime to an average of 30 minutes. If more complex distance units such as the travel time are used, the time can scale up to an hour or more for each individual run. It is recommended that if the Summarize Nearby tool is used, the spatial weight matrix should be prebuilt using ranges of drive time or distance, e.g., 5 minutes, 15 minutes, 30 minutes, and so on. The other tools that take a considerable amount of time in the model are the Spatial Join and Calculate Field tools. Both tools take more than two minutes combined due to the number of streets in the dataset.

If an error occurs, two tools in two separate groups would most likely be the reason the model has issues. The first tool is the Make XY Event Layer found within the Show Selected Crimes Within the City group. The crime data might not have the proper field name, and the model might not be able to create the point layers for future tasks. The next tool is the Spatial Join tool within the Spatial Join group. The Spatial join tool should be cross checked to ensure that the output fields that sum the count of crimes per street layer is connected to the proper fields in the data layer.

5.1.2. Hot Streets Results

The model was run multiple times, but only eight runs were shown in this final manuscript, which represent a variety of possible analytical efforts by the police force. Most of the crime points appear to be clustered at the eastern part of downtown Atlanta, north-east of the city, and the southwest which is close to the high crime neighborhoods of East Point and College Park. At the current scale of analysis which included only intersecting streets, no Cold Streets are found. Other runs which were performed at the early stages of the model that did not take account of street connectivity and used only Euclidean distance displayed cold spots, so it is safe to anticipate cold spots to appear once more streets are included in the spatial weights file. No cold spots were displayed for some of the runs when using the Optimized Hot Spot tool, which picks best aggregation levels to show maximum clustering. Therefore, the author is not overtly concerned that at the current scale of analysis, no cold streets were delineated.

5.1.2.1. Hot Street overlap with the Kernel Density

For all the Hot Street maps created, there is an overlay with the kernel density raster layer. The kernel density is divided into 6 classes just like the Hot Streets, and before the model was run it is expected that most of the Hot Streets would fall within high crime density areas. After analyzing the results from multiple runs, it appears that most of the Hot Streets appear in high density classes. When looking at the area of the different density classes to the number of Hot Streets, the higher density classes always provide the most Hot Streets per area. On the lowest density class, Hot Streets hardly occurred. A total of 26 out of over 4000 Hot Streets for all runs combined showed up at the lowest density class, but these streets were occasionally close to the next density class or had multiple crimes at the same street location. When looking at the kernel densities for Part 1 crimes, the Hot Streets that appeared at the lowest levels of the kernel density have a total length of 40 meters and five crimes with the same address at their intersection. The same streets showed up on the weekend run

5.1.2.2. Atlanta Part I vs Auto Theft and Larceny from Vehicle

The Part I crimes are compared with the street auto related crimes to see the difference in street related incidents. Auto Theft and Larceny from Vehicle crimes had an 83% match accuracy of crimes to streets, instead of the 81% match seen from Part I crimes. Using the Hot Street mapping for street related crimes such as Auto Theft and Larceny from Vehicle provides more Hot Streets in the high density classes when compared to Part I crimes. These closer locations within the higher density classes, and better crime to street matching percentages show that mapping street related crimes might be the best use of the Hot Street model.

5.1.2.3. Atlanta Part I vs Houston Part I

Atlanta and Houston Part I crimes were compared to see if there are similarities between the street classes the Hot Streets occur mostly in. After the analysis, the city of Atlanta has most of the Hot Streets within the service street class, followed by the residential street class, secondary, tertiary and finally the primary street class. For the city of Houston, most of the crimes occur in the secondary streets class, followed by the service, primary, tertiary, and finally the residential streets in order from the highest to lowest number of Hot Streets. This shows that different cities display different patterns, and after the tactical crime analysts find out the patterns and the associated street classes, they can present more information to the administrative crime analysis unit to aid the decision making process.

5.1.2.4. Police Shifts

The three police shifts (day, evening, and morning) are discussed because part of the tactical crime analysis unit's job is to provide crime pattern information to each unit at every shift and during briefings. The different shifts displayed different Hot Street patterns, but despite the differences, a few streets are highlighted continuously for all runs as well. Thirty-one out of over 330 generated Hot Street segments repeated at the 99% CL for all police shifts. Of those repeating streets, 27 are unnamed service streets, 2 tertiary streets, and 2 residential streets. The tertiary streets that displayed across all shifts are named Stone Road Southwest and Perry Boulevard Northwest. The residential streets are named North Desert Drive South West and an un-named street. Giving the officers the specific streets can help in the reapplication of a crime control tactic, or display the inefficiency of the crime control method deployed in the area.

5.1.2.5. Weekday vs Weekends

There are different associations between people and their environments between weekends and weekdays, especially when observing travel patterns. The weekends show a 2% increase in crime patterns on residential streets and a reduction of Hot Streets found in other classes. When observing the changes at some locations on the map, the Hot Streets generated on the weekend are also closer to the lively streets of the city which have bars and other nightlife offerings located on them.

5.1.2.6. Atlanta Hot Street Result Conclusion

The service roads class contains over 80% of all the identified Hot Streets, and repeated Hot Streets at different crime shift. As stated earlier, the service roads include alleys, parking aisles, and other access roads. With this finding, a possible approach that can be taken by the police department is crime prevention through environmental design combined with police patrols. Crime prevention through environmental design (CPTED) is a collection of principles that encourage safer areas by discouraging criminal actions. Examples of CPTED that can be applied in this study are alley gating and natural surveillance. Gating alleys reduce the crime opportunity presented to criminals by making it harder for them to commit crimes through reduced to no accessibility. In a study performed in Oldham, North West England; alley gating significantly reduced burglaries incidents (Haywood et al. 2009). A literature review of 11 street and alley closures at several cities from the year 1973 to 2000, also indicate that there is a notable crime reduction of different crime types in each study area (Clarke 2005). Increased natural and video surveillance are also possible options that can be taken to mitigate the crimes that occur in these unsafe environments. The identification of these locations helps the police officers know what service roads to keep an eye on during patrols, and citizens avoid during commutes to and away from homes.

5.2. Limitations

One of the most significant limitations to this analysis is the accuracy of the crimes in the excel data provided by the police department. The officer's file reports with the nearest streets address and drawings which can contain a significant amount of human error, especially when it is typed again before being placed within the police database. Since the officers do not use GPS equipment to log the crime locations, it is up to the analyst to use the address and drawing to determine the best-approximated location of the crime occurrence. The crime addresses sometimes do not match the street names due to shortening of names such as writing SW instead of Southwest in the report.

Street segments sometimes do not have names attached to old and newer routes which may appear in police reports. There is also an issue with streets that do not intersect with any other linear feature because the street layer still needs to be updated and properly connected.

5.3. Future Research and Recommendations

Although this model fulfilled the goal of creating an effective means to depict crime patterns for intersecting streets, there are still several improvements that can be made to the methodology. One of the recommended improvements is an increased study area. The study area should be increased beyond the city limits because sometimes the police respond as backup to crimes outside but very close to the city limit boundary. Under this circumstance, the officer might be responsible for filing a report because there are no hard lines showing the boundaries especially for properties on the border. Increasing the clipped area beyond the city limits and adding crimes of nearby cities on those street segments also make those streets represent more accurate patterns on the edge of town.

Secondly, for this tool to be efficiently used by crime analysts around the United States, it will need to be integrated into the records management system (RMS) currently used by the police, so the analysis can be automated and constantly added to the automatically developed map layers. This is important for the officers because they will not only see the Hot Streets immediately but have the full police report for each crime that occurred in that location. This provides the police officer with both the street names and possible suspect information. The integration into the RMS system will also enhance the iteration of the model to provide updated results with real time crime occurrences constantly.

5.4. Conclusion

The Hot Streets are created with the use of the Getis-Ord Gi* statistic from the HSA model tool. The HSA model successfully provides a high level of precision for observing crime patterns on each street. The model also offers increased flexibility for tactical crime analysis teams, as it can work on several scales and in different study areas. It is important to note that broadening the number of street neighbors lead to an increase in the analysis run time. There are only 3 model inputs which can be downloaded freely from multiple sources like the U.S. Census Bureau, city GIS, and Police departments. With over 80% spatial joint accuracy of the crimes to the nearest streets, most of the Hot Streets per area appeared within the higher crime densities in all study areas and presented Hot Streets in different street classes. This model has proven to be an efficient tool that people of all experiences and levels can use for the identification of micro-clustering of crimes through Hot Streets. The model may also have potential application in point to polyline studies such as car accident patterns and vehicle air pollution.

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Appendix A: Detailed Model Screenshots

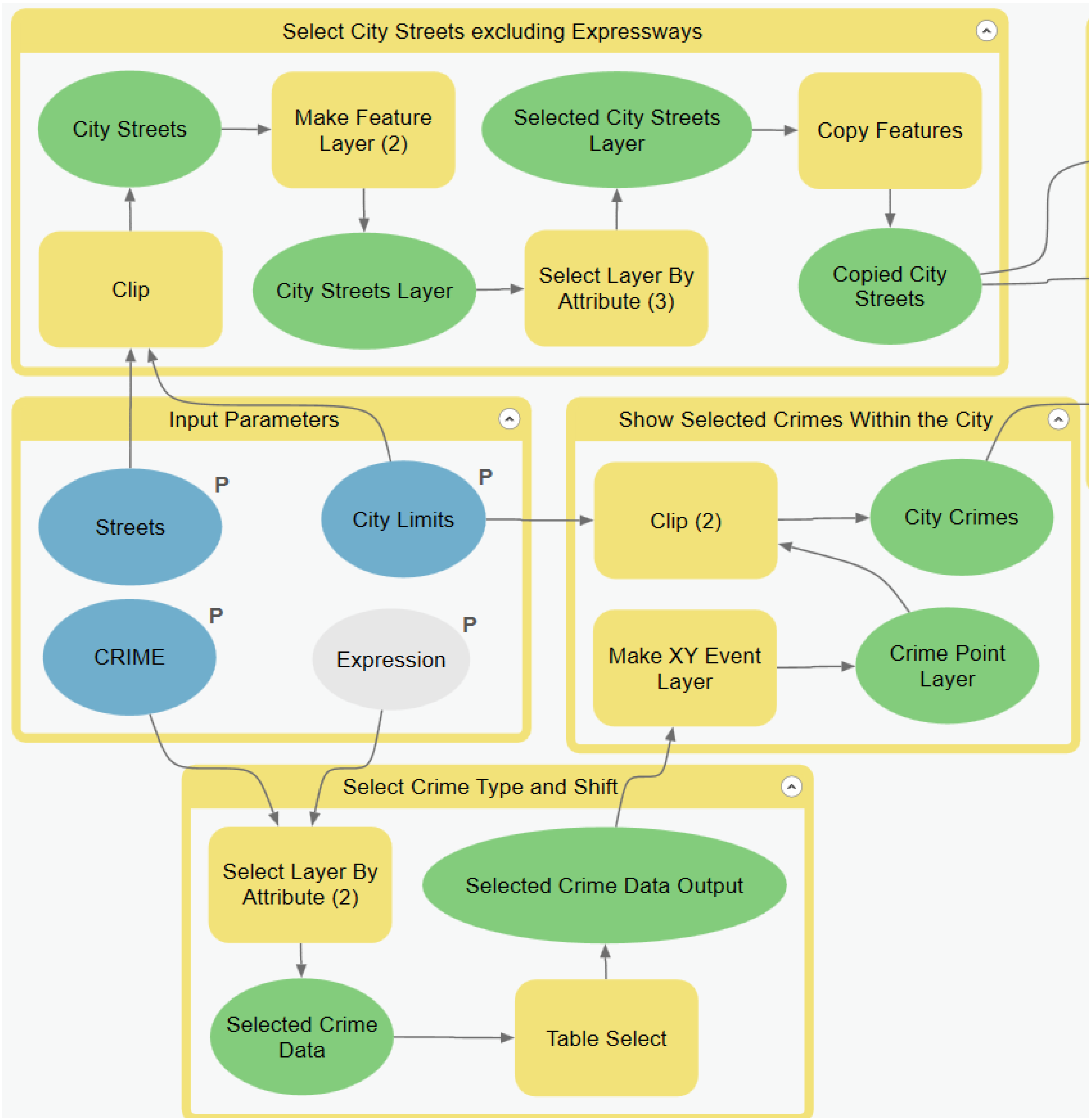

Figure 21. First four model groups

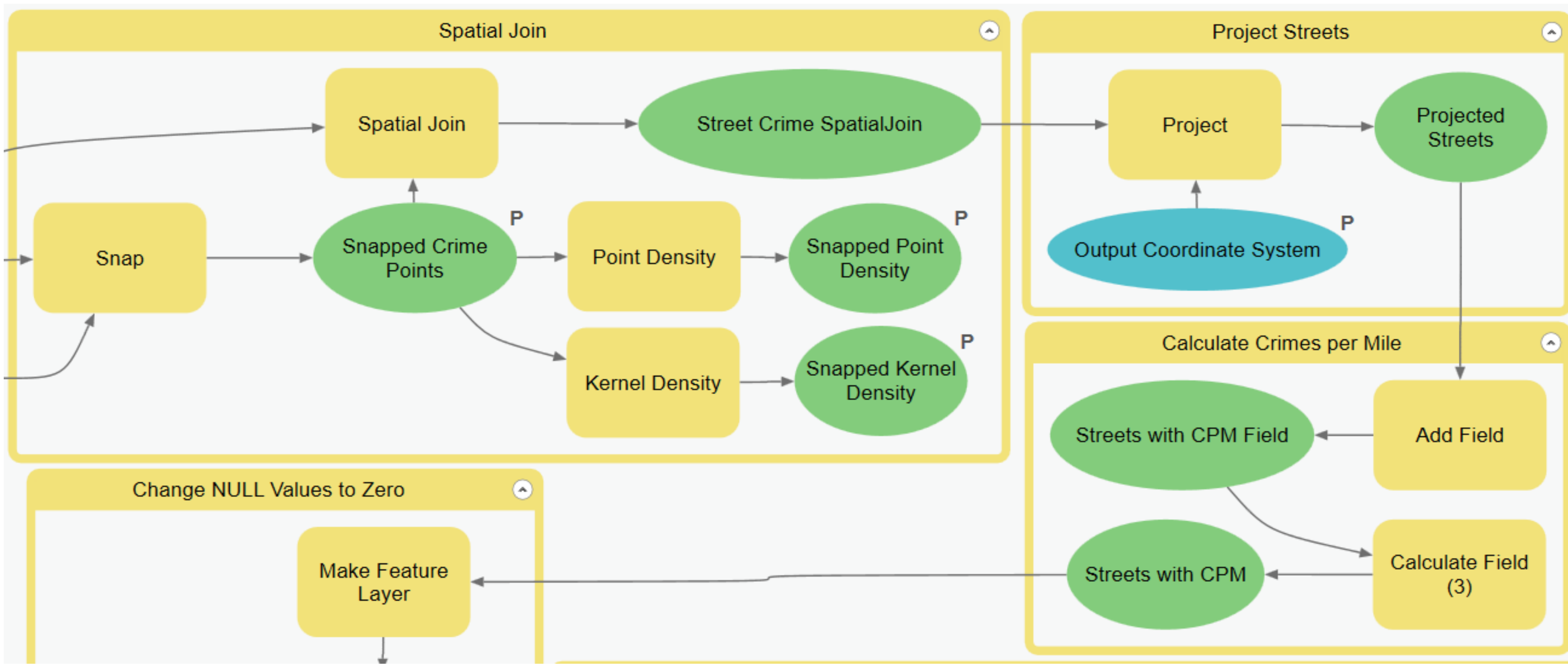

Figure 22. Central model groups

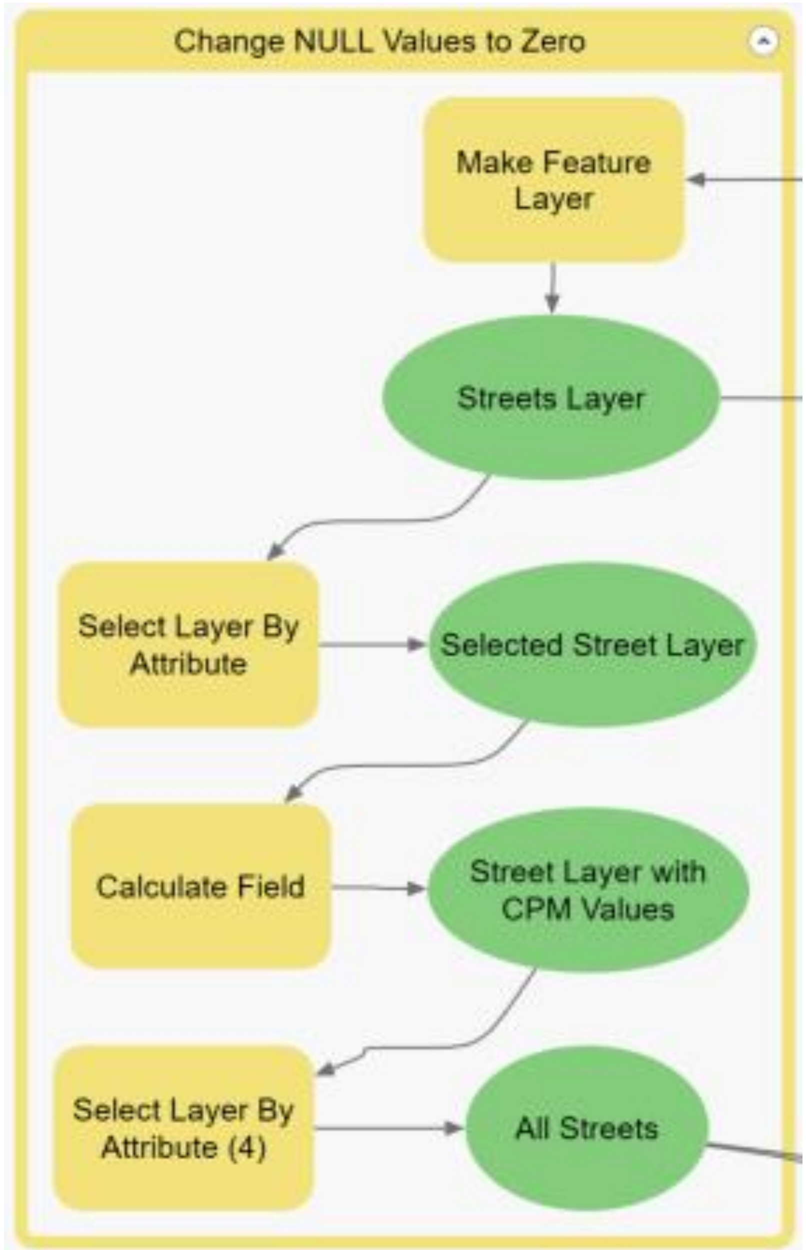

Figure 23. Change Null Values to Zero group

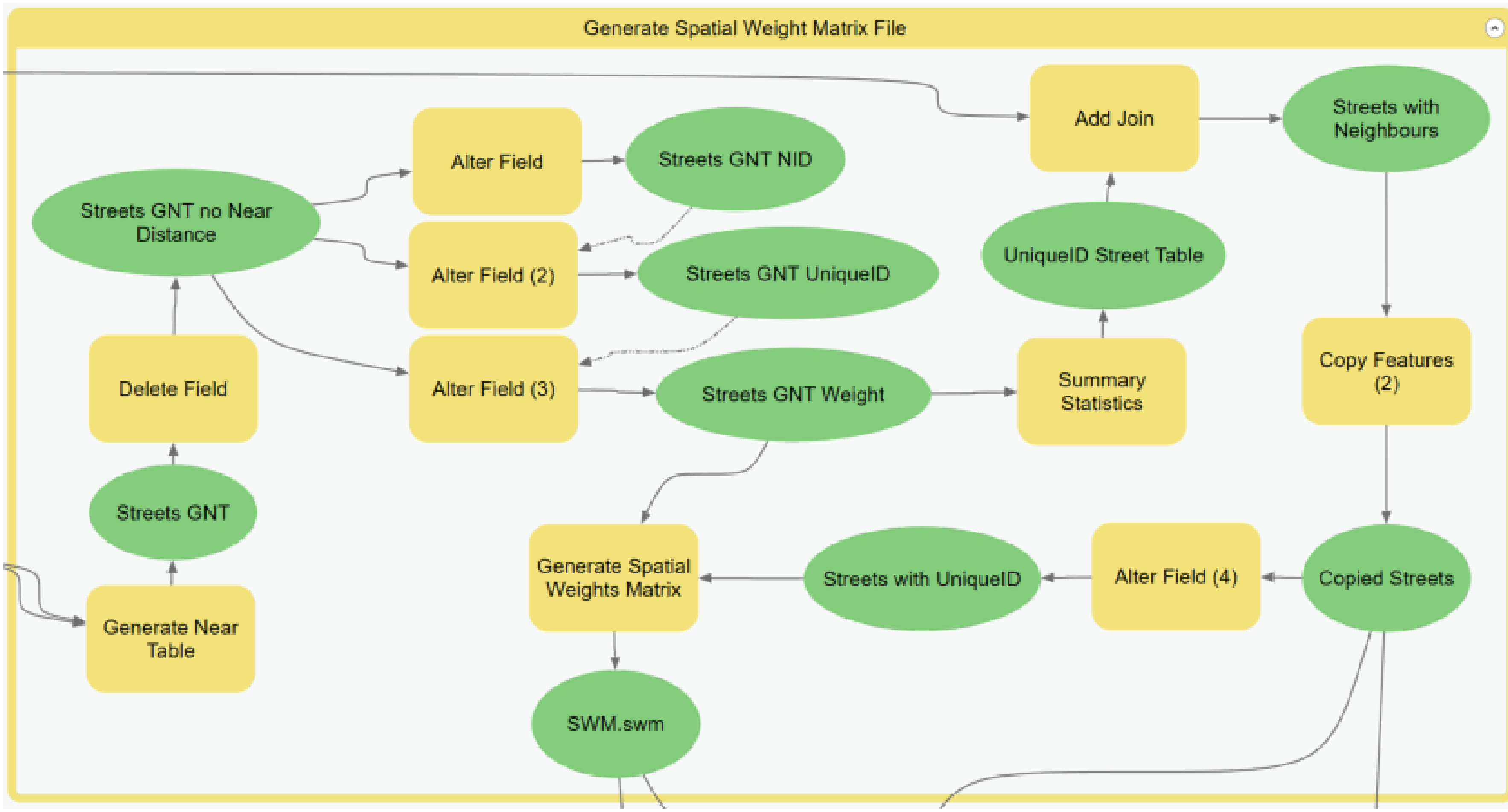

Figure 24. Generate Spatial Weight Matrix group

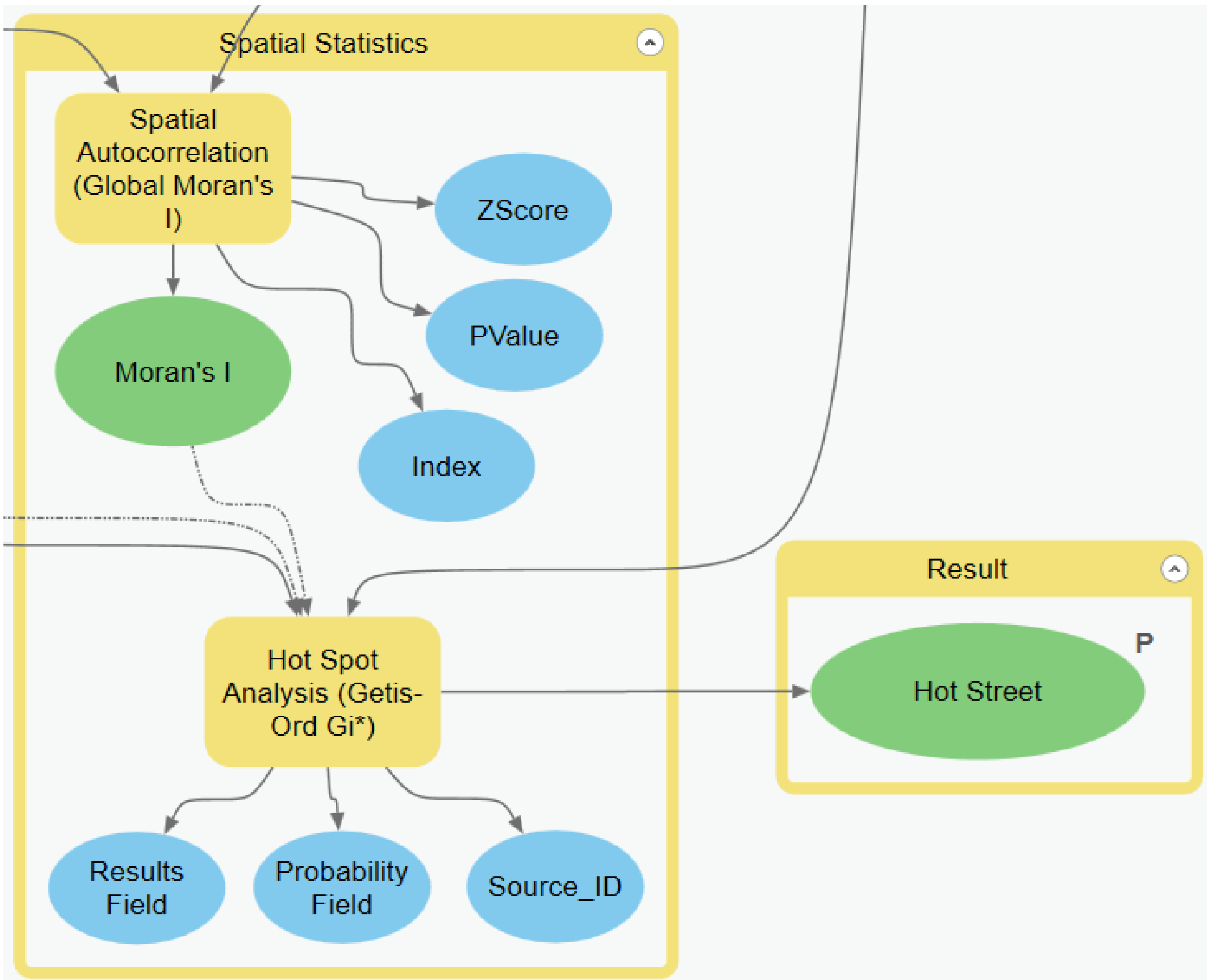

Figure 25. Spatial Statistics group