5-2016

Does crime correlate with fear?: Analyzing the Spatial Relationship between Perceptions of Safety and Crime using Sketch Maps and Geographic Information Systems (GIS) in the Main South Neighborhood of Worcester, MA

Marina Khananayev
Clark University, mkhananayev@clarku.edu

Does crime correlate with fear?: Analyzing the Spatial Relationship between Perceptions of Safety and Crime using Sketch Maps and Geographic Information Systems (GIS) in the Main South Neighborhood of Worcester, MA

Marina E. Khananayev

MAY 2016

A Master's Project

To be submitted to the faculty of Clark University, Worcester,
Massachusetts, in partial fulfillment of the requirements for
the degree of Master of Arts in the department of Community Development & Planning.

And accepted on the recommendation of

Yelena Ogneva-Himmelberger, Chief Instructor

ABSTRACT

Does crime correlate with fear?: Analyzing the Spatial Relationship between Perceptions of Safety and Crime using Sketch Maps and Geographic Information Systems (GIS) in the Main South Neighborhood of Worcester, MA

Marina E. Khananayev

The relationship between reported crime and residential perceptions of safety is understudied and inconclusive due to its highly complicated nature. This study seeks to narrow this gap by using sketch maps collected from residents about their safety and crime data. Two methods, one visual, the other statistical (Bivariate LISA), were tested using data from sketch maps drawn by about 95 survey respondents and crime data spanning three years (2011-2014). Data was disaggregated by gender, age, and length of residency. Visual analysis of results show that perceptions of safety occur at a fine scale. Respondents marked sketch maps at varying scales and attached their perception to features such as parks, street names, and street corners. Therefore, the method chosen for statistical analysis of this relationship was unable to capture these nuances and was deemed ineffective. However, the visual results show emerging patterns and suggestions for future collection and analysis of data are recommended.

Yelena Ogneva-Himmelberger, Ph.D.
Chief Instructor

Laurie Ross, Ph.D.
Second Reader

ACADEMIC HISTORY

Name (in Full): Marina Elizabeth Khananayev Date: May 2016

Baccalaureate Degree: Bachelors of Art in Geography

Source: Clark University, Worcester, Massachusetts Date: May, 2015

TABLE OF CONTENTS

1. Introduction

The field of crime research has historically been dominated by experts studying the occurrences of reported crimes from a quantitative perspective in urban environments, in most cases as a way to target strategies to reduce crime. However, recently, researchers are beginning to acknowledge the knowledge gap that this framework creates in a field of research so complex and multi-layered. Since the 1950's and 60's, geographers, criminologists, and urban planners alike have begun to examine the impact that perception has on the way humans interact with their environment. Even more recently, researchers are beginning to examine the ways in which perceptions of crime differ spatially, with the use of Geographic Information Systems (GIS). Past research about fear of crime in the United States, which is often conducted on a large scale in the form of quantitative surveys, has found that people tend to have higher perceptions of crime, even though crime rates have been decreasing (Ferguson and Mindel 2007). However, these claims often lack a nuanced understanding of the spatial variations that occur at the neighborhood level in an urban context. Researchers and larger institutions such as the National Institute of Justice are beginning to develop methods to analyze crime and perceptions of safety at the neighborhood level through the use of GIS (Wilson et al. 2009; Curtis et al. 2014).

Why is fear of crime important to understand in the context of urban neighborhoods? Warr et al. notes that fear of crime itself is not necessarily a negative thing, as it can lead to increased protection and higher levels of safety for an individual or a group of people (2000). However, when this fear is no longer at the same level as objective risk, the consequences may have serious implications for individual and neighborhood-level vitality (Warr et al. 2000; Jackson 2011). These consequences include theories such as the well-known Broken Windows theory (Wilson and Kelling 1982), implications for individual and neighborhood level health (Lorenc et al. 2012), and potential issues for urban planners, community-based organizations, and stakeholders interested in improving neighborhoods.

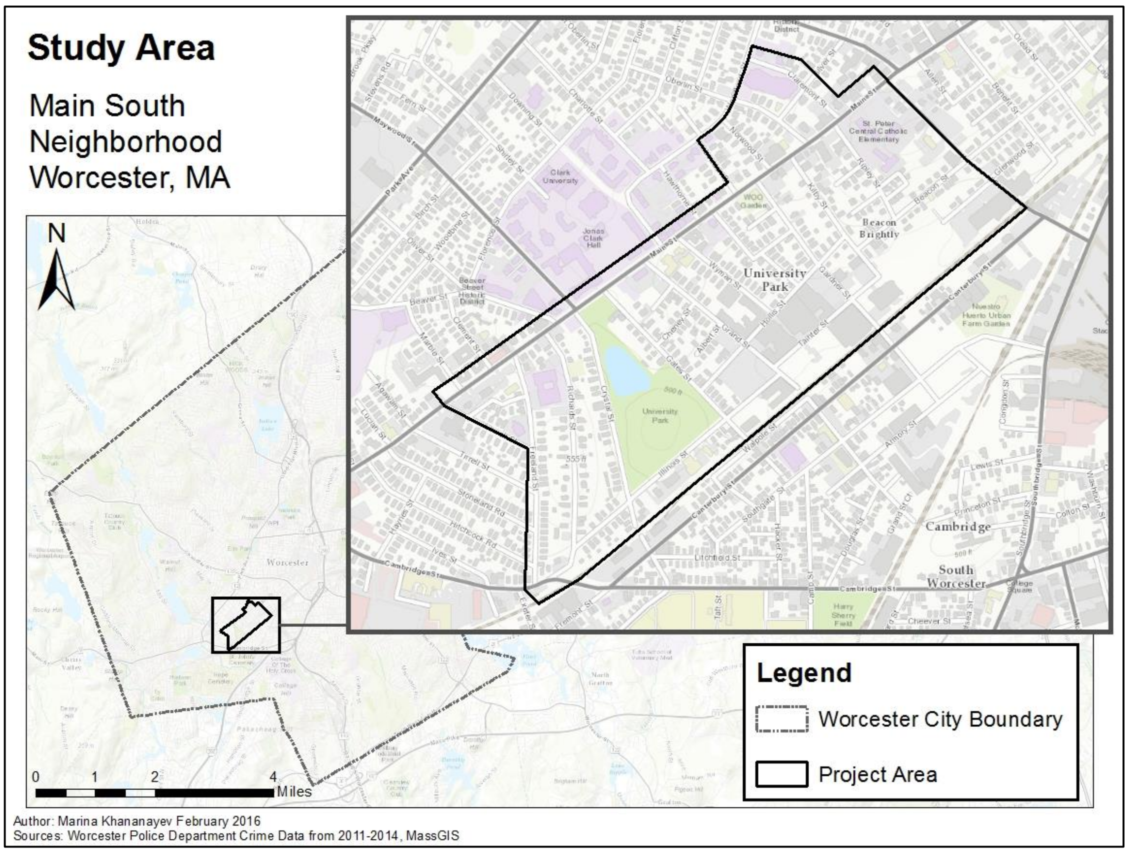


Figure 1. The study area is located on the south side of Worcester and encompasses a public park as well as residential homes, schools, churches, and businesses.

1.2 Project Background

Located in the Main South neighborhood in Worcester, Massachusetts, exists a 13-acre park known as Crystal, or University Park with a long history of crime and violence (see Figure 1). Despite efforts to revitalize the area, including a $1.5 million dollar renovation carried out just five years ago in 2011, a stigma of violence around the park still exists. This stigma has led residents to interact with the park and surrounding neighborhood differently, which could pose a threat to the vitality of the area.

In October 2014, the Main South Community Development Corporation (CDC) received a grant of about $1 million from the Byrne Criminal Justice Innovation (BCJI) Program from the Department of Justice in order to address the problems that still persist in the Crystal Park neighborhood. This particular area received the BCJI grant out of a pool of about 100 applicants from urban communities across the United States along with 16 others due to the hotspots of crime found in the area and the applicant's ability to create a comprehensive plan to revitalize the neighborhood through community-based research and effective implementation with strong and active community partners.

Throughout the planning phase of the project, community partners such as the neighborhood's Boys & Girls Club, the CDC, the city's police department, and a university research partner located across the street from the park teamed up with residents in order to carry out an extensive analysis of the area to inform their implementation phase. Research methods chosen included literature reviews, in-depth media analyses on how the Main South neighborhood is perceived, a GIS-based hot spot analysis of crime, a door-to-door household survey with a series of questions about neighborhood perceptions and sketch mapping exercise, analysis of Byrne in the context of other revitalization efforts, and the creation of neighborhood-based working groups to interpret findings and translate them into strategies.

While this current study solely analyzes perceptions of safety as they relate to reported incidences of crime, the findings have practical implications for neighborhood improvement strategies. This research has been carried out in the hopes that the larger research team in the Byrne project will use the findings to inform strategy and implementation.

1.3 Literature Review

This literature review will first examine the ways in which social scientists have defined fear of crime in addition to analyzing theories that support the importance of studying fear of crime. Next, we will explore the ways in which researchers have hypothesized about the different factors that influence perception of one's environment. Lastly, we will provide an overview of the history of sketch mapping and the methodology that currently exists for spatially examining perceptions of safety and crime with the use of sketch maps integrated into GIS.

Fear of crime

It is important to note that the earliest crime research solely focused on reported crime. While this research is incredibly important to informing crime-reduction strategies, examining the way people perceive, and therefore interact, with their environment is also important to consider as well, and may even play a role in affecting actual levels of crime (Burgess 1970; Bruce and Burgess 2011). While crime plays a role in affecting perceptions, the degree to which this is true is currently understudied and inconclusive, especially when examined from a geographical perspective.

Factors that influence fear of crime

While previous victimization has been heavily researched and proven to be a strong determinant for increasing fear of crime (Ferraro 1995), there exists other, less apparent factors that may come into play when examining a person's geography of fear in the urban context. There is no doubt that humans are complex beings and that their emotions, especially surrounding fear, are difficult to understand. However, the emerging body of extant knowledge on this topic divides factors that may influence fear of crime into three main categories: 1) environmental cues, 2) demographic factors, and 3) social dynamics.

Environmental theories about fear of crime point to a variety of external factors that may trigger an emotional response interpreted as fear. Physical cues such as incivilities or signs of social disorder may play a role in the way that people fear a space

(Perkins et al. 1992). This may include the presence of trash, graffiti, abandoned buildings, poor lighting, loitering, etc.

Certain demographic groups may feel more vulnerable in their environment than others (Doran and Burgess 2011; Lagrange and Ferraro, 1989). For example, past studies have found that while men are most likely to be victimized in crimes, their perceptions of fear are often far less than other demographic groups, especially women (Brownlow 2004). Many studies have examined the role that gender and age play in perceptions of safety, with mixed results (Clemente and Kleiman 1997; Scarborough 2010; Breetzke and Person 2014)

Social dynamics, otherwise known as neighborhood structure, is also a factor that plays into theories about influences on crime. Some studies have shown a strong neighborhood structure and social cohesiveness leads to a reduced fear of crime (Taylor et al. 1984). This relates to our current framework because studies spanning multiple disciplines have found that length of stay in a neighborhood plays a role in establishing social cohesiveness and integration (Forrest and Kearns 2011; McMillan and Chavis 1986; Kasarda and Janowitz 1974). However, the topic remains contested as others have found this factor to be insignificant in when analyzing geographies of fear (Kanan and Pruit 2002).

GIS methods for comparing perceptions of safety to reported crime

The groundwork for establishing the legitimacy of participatory mapping has been laid by prominent geographers in the past few decades (Lynch 1960). However, of all the techniques that have been and are currently being explored and tested, sketch maps remain to be one of the most popular, yet most contested tools used, especially when used to analyze geographies of emotion. Cognitive mapping has traditionally been used as a way to document an individual's perception of their physical and social environment (Nasar 1998). Examples of this can be seen in the works of Ladd (1970), Hirtle and Jonides (1985), King (2002), in the extensive work that has been done to map peoples' perceptions of geographically defined elements of the environment such as neighborhood boundaries, community resources, or land-use activities. Now, geographers are beginning to test methodologies that analyze emotions in the form of sketch maps and GIS (Pearsall et al. 2015; Boschmann and Cubbon, 2014; Kwan 2007).

One emotion that has been looked at from a geographical lens more closely than most, probably due to its practical applications in society, is fear (Nasar 1998; Doran and Burgess, 2011; Curtis et al. 2014). Fear mapping is the technique that geographers use to analyze people's spatial perceptions of fear. This has been operationalized in a multitude of ways in the methods and language used to ask people about "fear". The most common and promising methods that exist use terms such as "unsafe" (Ceccato and Snickars 2000; Kohm 2009; Lopez and Lukinbeal 2010), "comfort" (Matei, Ball-

Rokeach, and Qui 2010), and avoidance mapping (Doran and Lees 2005) in order to ask people about their geographies of fear.

Despite the importance that scholars have placed on analyzing fear of crime, a literature review of GIS methods used to analyze the relationship between crime and fear of crime at the neighborhood scale returned very few results. Virtually zero published articles have developed a legitimate framework that statistically analyzes the relationship between crime and perceptions of safety. Analytical methods varied from study to study in the form of purely visual and descriptive tools, to statistically rigorous tools. The following methods and studies are highlighted in order to combine different aspects of varying tools in order to set up the methodological framework for our work. Lopez and Lukinbeal (2010) use a method of aggregating polygons to grid cells about the size of a block in order to compare police perceptions of high crime areas to resident perceptions of safety. Residents were given guidelines for definitions of “safe” and “unsafe” areas such as “areas where they visited friends, interacted with community members, or were familiar with or felt comfortable going to” and “blight and crime issues, dark streets, and provoked a general feeling of discomfort” respectively (Lopez and Lukinbeal 2010: 41). Police were given slightly different instructions and asked to mark where their perceptions of “low” and “high” crime areas. Their result was a simple visual analysis of blocks where crime overlapped with perception and where police and resident perception overlapped as well. Results from this study found that police perception was more heavily influenced by reported crimes and that residents were perceiving crime in areas where no reports were generated.

Curtis et al. (2014) tested several different methods for integrating sketch maps of fear in Los Angeles gang neighborhoods with GIS in both a visual/descriptive and statistical way. In 2007, as part of a larger neighborhood revitalization project, researchers surveyed 214 male youth from ages 14 to 21 in three Los Angeles neighborhoods. Survey respondents were asked to mark an “X” if they were fearful of going to that place. Maps were then digitized in the form of both point and polygon files, in order to analyze the difference in results between the two methods. Curtis et al. (2014) employed four methods to analyze the sketch maps collected: 1) descriptive statistics of maps (in terms of number of spaces, mean and median area of spaces, and spatial pattern), and then using more analytical tools in GIS, 2) aggregation to parcels and grid cells, 3) univariate local indicators of spatial autocorrelation (LISA); and 4) kernel density estimation (KDE) and a spatial filter. The authors are extremely critical of their methods and identify many limitations to this work, however, important contributions to the field emerged. The first was the idea of transparency. Because methods for this work are so diverse, it is important that researchers represent their methodology in the most honest and detailed way, in addition to being critical of the limitations. Secondly, Curtis et al. notes the promise that aggregating perception maps to grid cells has, due to the freedom with which respondents can identify their fears in the form of points or polygons. Lastly, in relation to our study, Curtis et al. notes the importance of disaggregating data by different respondent variables, in order to examine the spatial variability that may be influenced by these factors. The authors conclude by noting that much more work must be done in order to develop a proper framework for analyzing perceptions of fear and that any future studies done should focus on transparency in methods and analysis.

1.4 Research Questions

Today, there clearly remains a gap in knowledge on how to operationalize and understand the geographies of fear. While researchers are taking strides to close this gap, there appears to be a lack of consensus on the best methodologies to use in order to compare perceptions of safety to the occurrence of reported crime. This paper seeks to test a methodology for analyzing this relationship guided by the following research questions:

1. To what extent do perceptions of safety correlate with the occurrence of reported crimes in the Main South neighborhood of Worcester, MA?
2. Is the correlation between perceptions of safety and the occurrence of reported crimes at all influenced by gender, age, or length of residency?

This project sought to compare resident perceptions of safe and unsafe areas from survey results with crime data compiled by the Worcester Police Department. The three main components of the research methodology are listed below and will be described in more detail throughout the data and methods section.

1. *Spatial representation and analysis of crime data.* This component is based on crime data provided by the Worcester Police Department from 2011-2014 and was spatially represented using the Kernel Density tool in GIS.
2. *Survey data collection and analysis.* Survey data from the BCJI implementation research collected in 2015, including sketch maps collected from 146 residents were split by gender, age, and length of residency, digitized, and analyzed using GIS.
3. *Comparison of survey data and crime data: two methods.* First, a visual comparison of crime and perception was done at a fine scale of 7 ft. by 7 ft. Second, using a coarser scale of 100 ft. by 100 ft., maps were statistically analyzed to understand the spatial relationship between reported crime and perceptions of crime in the Crystal Park neighborhood using the Bivariate LISA analysis.

2. Data

2.1 Police Reported Crime

Data on reported crimes for the city of Worcester was provided by the Worcester Police Department (WPD) from the years of 2009-2014 in the form of an

Excel spreadsheet. Records included information on type of crime, descriptive information on each person involved in the incident, date and time, and addresses for each incident. For the analysis, we wanted to examine only social disorder incidents and violent crimes, in order to exclude crimes such as fraud, which do not tend to be perceived by the public and could have skewed our results. For this reason, all crime incidents were grouped into two categories: violent crimes (robbery, aggravated assault, murders, and gunshots) and social disorder crimes (destruction/damage, vandalism of property, drug/narcotic violation/drug equipment violation, prostitution, disorderly conduct, and trespass of real property). The reported crime mapped includes places where there was either a victim involved or an arrest made. The crimes that were associated with victims were important to include because even though some incidents did not result in arrest, potentially due to a variety of reasons, these incidents may still influence perceptions of safety in the neighborhood.

In order to understand spatial patterns of crime, each reported crime was mapped using the Worcester Address Locator, which has an accuracy of about 90% at matching addresses with spatial locations in GIS. The remaining 10% of addresses were manually verified and mapped. We selected incidents spanning four years from 2011-2014 because most respondents indicated that they have lived in the neighborhood for at least four years (see figure with demographic info on respondents). The result was one shapefile containing crime point data for incidents involving either (and in some cases both) a victim or arrested person, categorized as social disorder crimes and violent crimes from 2011-2014. In total, there were 15,044 social disorder crimes and 5,740 violent crimes reported and mapped for the whole city of Worcester from 2011-2014. However, of those city-wide numbers, 1,516 social disorder crimes and 641 violent crimes reported were located within 1,000 feet of the Byrne project area. From these crime reports, we then deleted any points that represented the same incident. For example, multiple points were generated for the same spot on the map if both a victim and an arrested person were involved, or if one person was charged with multiple crimes. However, some points do overlap because there were multiple incidences occurring at different times at that location. Therefore, we ended up with 2,157 points that represent unique incidences of social disorder and violent crimes in and around the project area (see Figure 2).

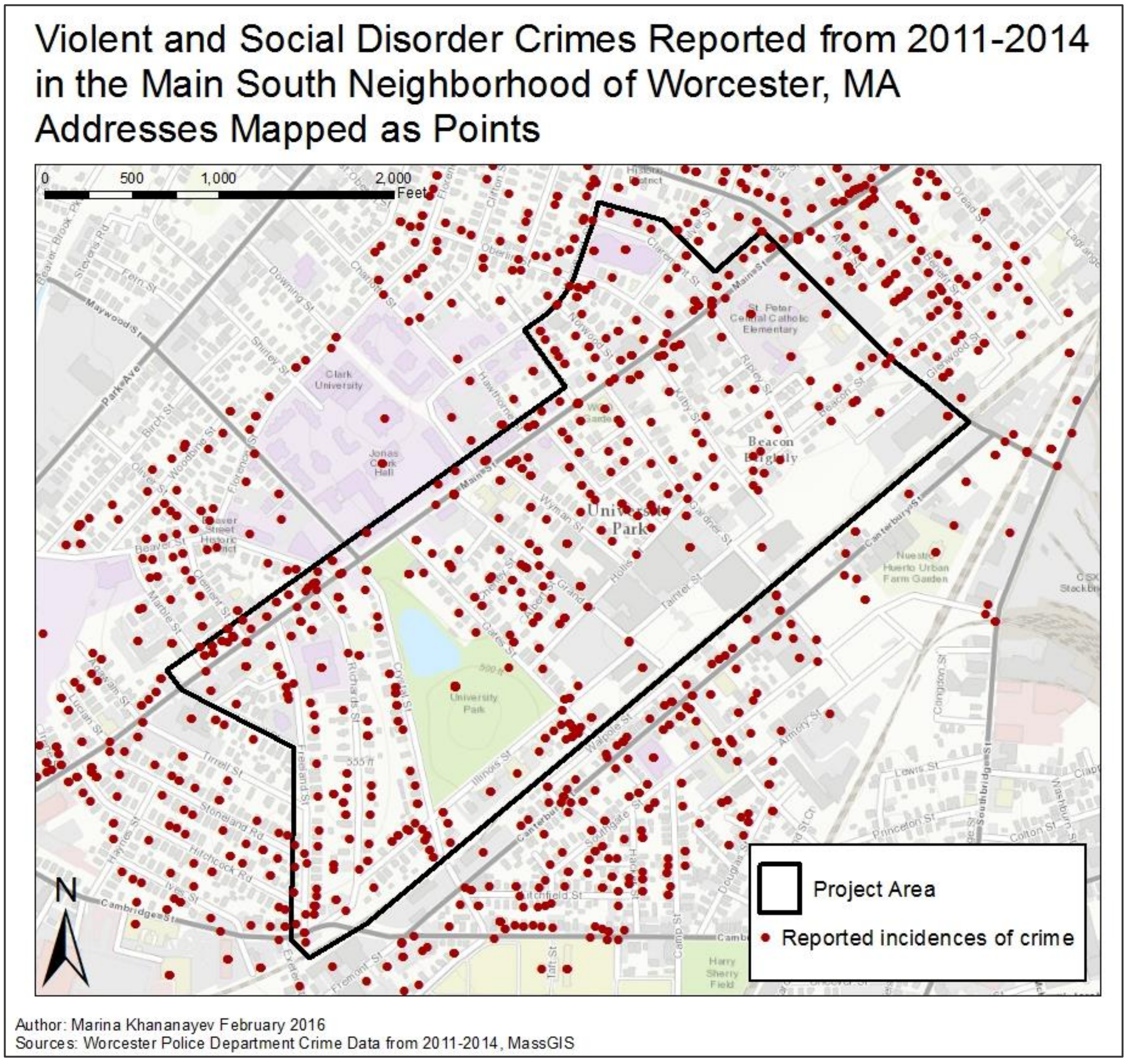


Figure 2. Crime incidences categorized as violent crime (eg. robbery, aggravated assault, murders, and gunshots) or social disorder (eg. destruction/damage, vandalism of property, drug/narcotic violation/drug equipment violation, prostitution, disorderly conduct, and trespass of real property) from 2011-2014 geocoded using the Worcester Address Locater tool.

2.2 Byrne Survey

As a part of the BCJI project, the research partner created an extensive survey to collect both quantitative and qualitative information from residents about their perceptions of the neighborhood in order to most effectively develop strategies to achieve the goals of the project. From June to August 2015, trained survey interviewers targeted community events and meetings, as well as churches, schools, the Boys and Girls Club, and households in the neighborhood and collected completed surveys from 146 residents, including youth. It is important to note that the survey was translated into both Spanish and Vietnamese in order to capture a more representative sample of the population.

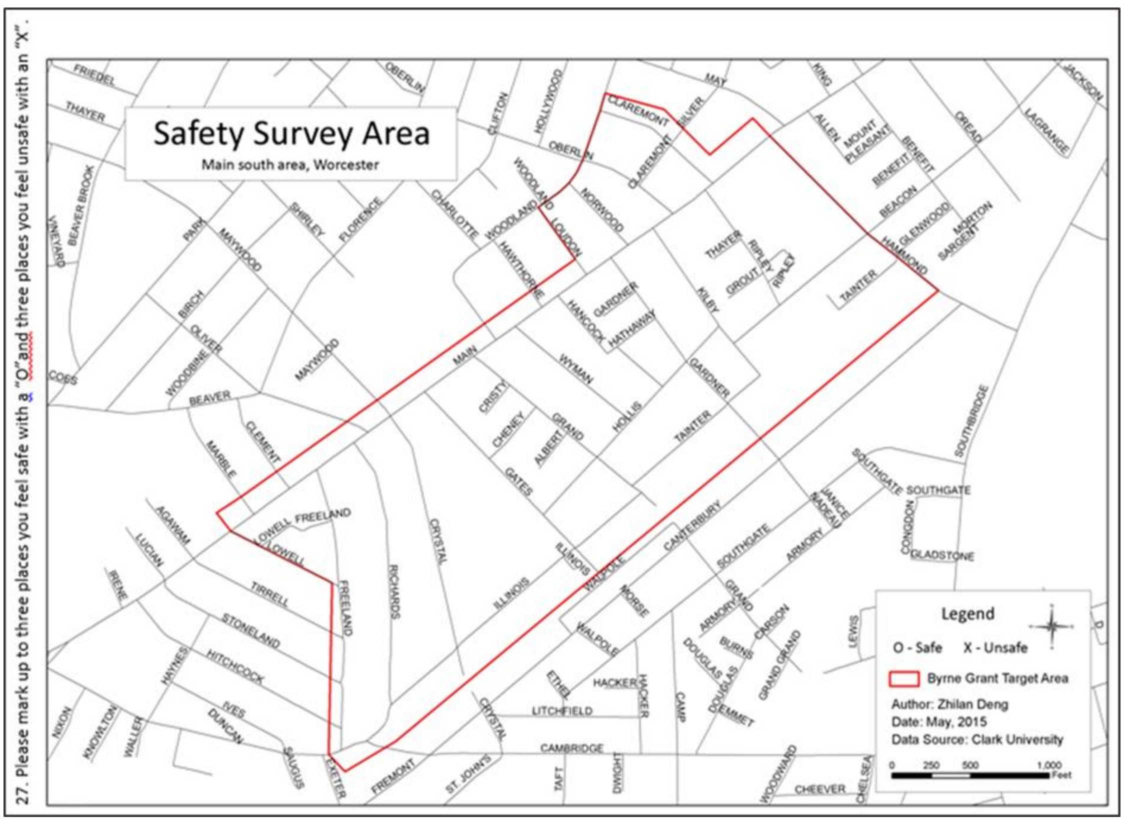


Figure 3. Example of the blank map included at the end of the Byrne survey

For the purposes of this research, our in-depth analysis will examine the final component of the survey. In this final portion of the survey, respondents were asked to mark 3 areas where they felt safe and 3 areas where they felt unsafe on a blank map that encompassed the project area, as well as a buffer zone of roughly 2,000 feet around it. Respondents were told to mark what they perceived as safe areas with an “O” and what they perceived as unsafe areas with an “X”. See Figure 3 for an example of the blank map that was included in the survey. Out of the 146 surveys collected, 80 people marked a total of 194 safe areas and 63 people marked a total of 158 unsafe areas. This may be due to the fact that the mapping portion of the survey was on the very last page of the survey or because respondents indicated they didn’t wish to provide this information due to time restraints or other unknown reasons. See Table 1.

Table 1. Number of respondents who filled out the quantitative portion and the mapping portion of the survey.

	Surveys (total)		Surveys (***with*** sketch maps)	
Characteristic	**Number**	**Percent**	**Number**	**Percent (of all surveys)**
	n = 146		n=95	65%
Gender				
Female	93	*64%*	54	*58%*
Male	50	*34%*	34	*68%*
Other or left blank	3	*2%*		
Ages				
14 to 24 years old	53	*44%*	26	*50%*
25 to 40 years old	27	*18%*	27	*100%*
40+ years old	41	*28%*	31	*76%*
Left blank	25	*17%*		
Length of Residency in Neighborhood				
Less than 3 years	44	*30%*	29	*66%*
4 to 10 years	55	*38%*	34	*62%*
Over 10 years	38	*26%*	23	*61%*
Left blank	9	*6%*		

3. Methods

3.1 Visual Representation of Crime Occurrence and Perceptions

In order to compare reported crimes in the form of point data and perceptions of safe and unsafe areas in the form of polygons, we employed a method of aggregating data to grid cells. We chose to use aggregation because in GIS, it is a methodological approach that can be used by all types of vector data and therefore, enables comparison amongst different types of vector files. Additionally, past studies have found this method to be a legitimate and effective way to compare such vastly different types of data (Coulton et al., 2001; Matei et al., 2001; Ratcliffe and McCullagh, 2001; Lopez and Lukinbeal, 2010). This aggregation was performed at two different scales: 1) fine (7 x 7ft. cells) and 2) coarse (100 x 100 ft. cells). The finer scale allowed us to analyze the results visually and understand the nuances of perception of safety and crime while the coarser scale allowed us to use a statistically rigorous tool called Bivariate LISA, which will be explained in greater detail below.

Crime. Once the data was cleaned up, categorized, and mapped as points, we produced a density map showing crime intensity as a continuous surface in the area. This method is useful because many of the points overlap, as multiple incidences sometimes occurred at the same location. Crime density was calculated using the Kernel Density tool in ArcGIS, which is a widely regarded tool for crime mapping (McGuire and Williamson, 1999; Williamson et al., 1999, 2001; Chainey et al., 2002; Chainey and Ratcliffe, 2005; Eck et al., 2005; Chainey 2013).

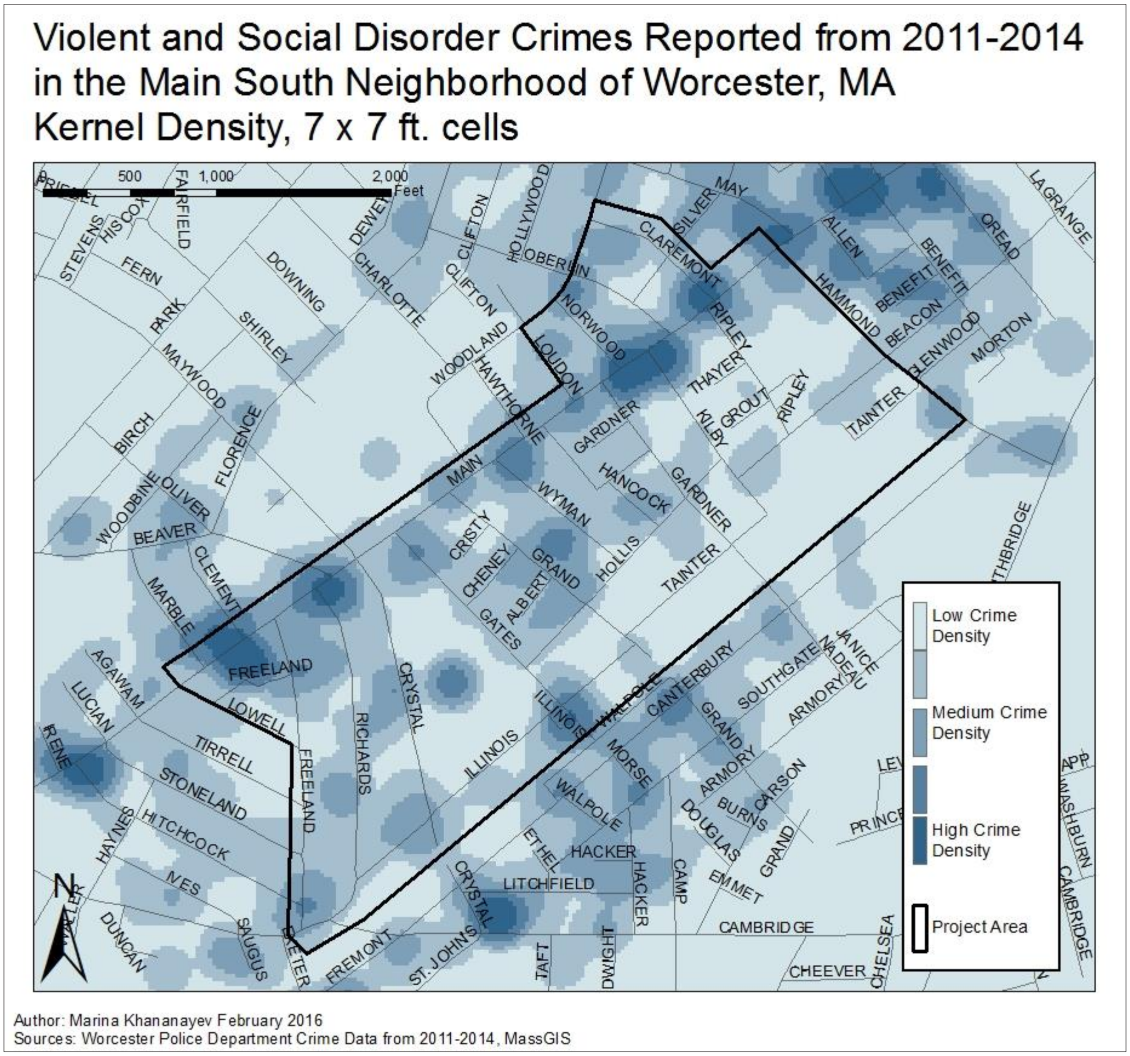


Figure 4. Crime density calculated using the Kernel Density tool in ArcGIS. Darker areas indicated a higher density of crime and lighter colors indicate a lower density of crime. Crime density was calculated for the 2,157 incidences of crime that fell inside and within 1,000 feet of the project area. This is why areas outside of this appear as if no crime happened there. There may have been crime occurring in these areas, however, our analysis was only concerned with a small-scale of crime.

The Kernel Density tool is a form of grid cell aggregation that is effective for capturing a continuous surface with data such as points of crime. Rather than simply counting the number of points that falls within each cell, it assigns each cell the value of the algorithm that calculates density. Essentially, the tool calculates the density of points by fitting a smoothly curved surface around each individual point of crime. The value of this surface is highest at the location of the point and decreases as the distance from the point reaches the extent of the search radius chosen. The density at each cell is calculated by adding the values of all of the kernel surfaces that overlay the cell. For our analysis we used a small cell size of 7 x 7 ft and a search radius of 70 ft., due to the small size of the study area. A smaller cell size and search radius displays more detailed and localized crime density areas (Chainey 2013). Visually, this shows places on the map with a darker color as having a higher intensity of crime and lighter colors representing a lower intensity of crime (see Figure 4). This map, showing crime at such a fine scale, was used to visually compare density of crime to perceptions of safety.

Figure 5. Example of a filled out survey map.

Sketch Maps. Sketch maps were then digitized using ArcGIS as ellipses that covered the areas that respondents marked. Since the survey asked respondents to mark both circles and X's, we chose ellipses to represent perceptions. This allowed us to digitize the variations of hand-drawn spaces as accurately as possible. See Figure 5 for an example of one filled out sketch map.

Ellipses were then split into separate shapefiles according to gender, age, and length of residency in order to determine if personal characteristics played a role in perceptions of the neighborhood. Past research has indicated that these factors play a role in how people perceive fear and crime (Hunter and Baumer, 1982; Taylor et al., 1984; Kanan and Pruitt, 2002; Doran and Burgess 2011). Gender was divided into male and female, age was split into three categories of *1)* 14-24 years old, *2)* 25-40 years old, and *3)* 40+ years old, and length of residency was split into three categories of *1)* <1 year to 3 years in the neighborhood, *2)* 4 years to 10 years in the neighborhood, and *3)* 10 or more years in the neighborhood. This was done using the "select by attributes" function in ArcGIS which created a total of 8 different shapefiles representing demographically different groups of people. In order to compare the relationship between crime and perception visually, frequency of safe and unsafe perceptions were mapped at a fine scale of 7 x 7 ft. cells, which maintains consistency with the crime density map. This was done a total of 18 times, which produced maps showing safe and unsafe area densities for all respondents, plus split into the 8 different groups of respondents described above (see Appendix for full list of all maps split by demographic).

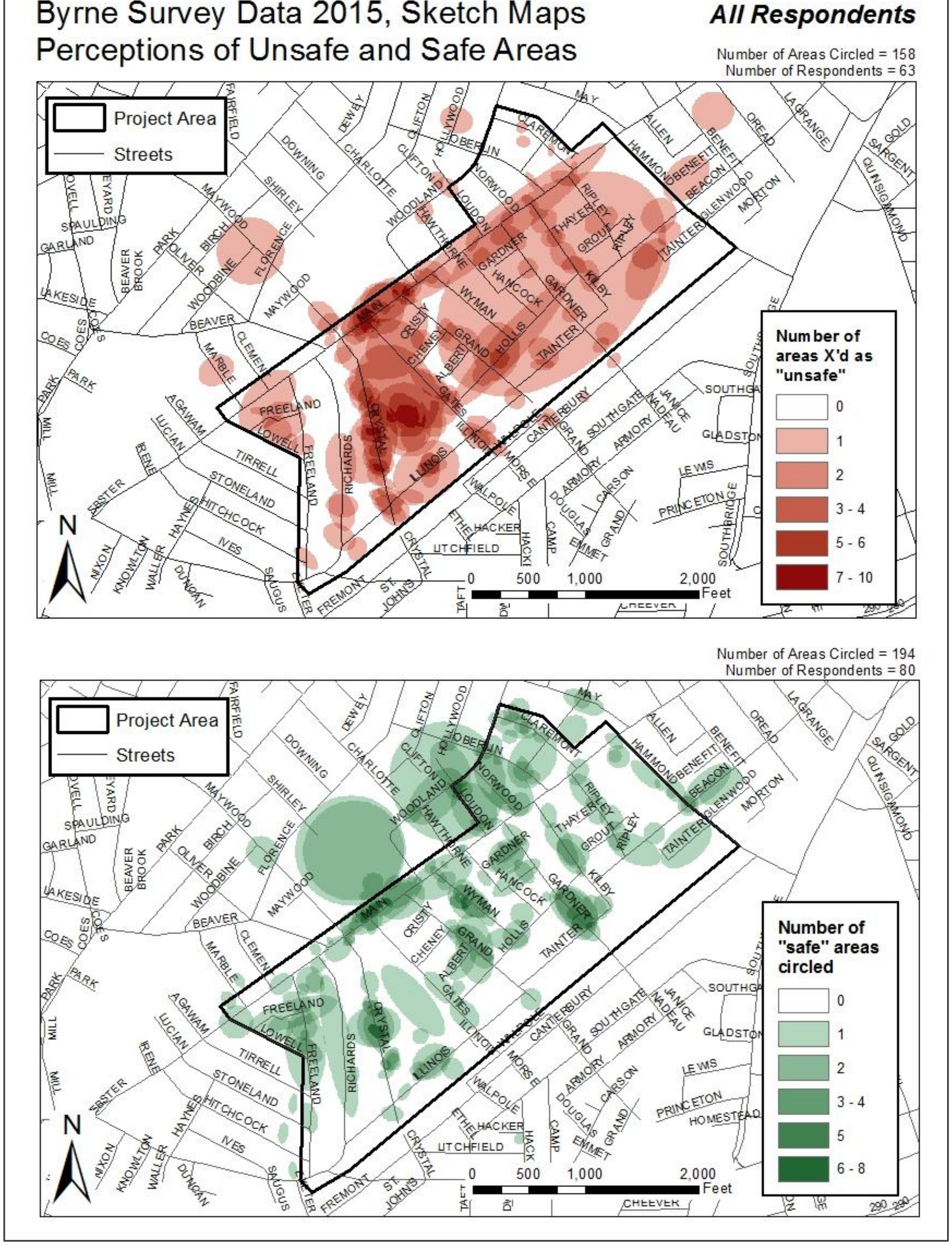


Figure 6. Sketch maps digitized to GIS as ellipses and joined to 7 by 7ft. cells to represent frequency of perceptions. Darker colors represent a higher number of observations in that area.

Digitized Sketch Maps and Crime Density. Comparison of maps was done visually by first identifying areas where crime density was concentrated in areas as medium or high. Then, areas where perceptions of either safe or unsafe areas occurred at high frequencies (the top two classes of out five) were compared with the medium to high density crime areas identified in the previous step.

3.2 Statistical Analysis: Bivariate LISA

The steps above provided us with a visual representation of the data, however, we wanted to examine the relationship between where respondents perceived safe and unsafe areas and where crime was being reported by the police department statistically. Therefore, we used a statistical tool called Bivariate Local Indicator of Spatial Autocorrelation (LISA) analysis in the program GeoDa, which measures bivariate local indicators of spatial autocorrelation, or the correlation between clusters of two variables. Developed by Luc Anselin (1995), this tool tests whether localized correlations between values of a feature and the values of that feature's neighbors are significantly above or below the mean of defined "neighborhood" (Anselin, Ibnu, and Kho 2006). However, the tool also takes into account the mean of the entire study area as well. The algorithm tests whether local correlations between values of a feature are significantly different from what would be expected from a complete spatial randomization. Essentially, "it identifies significant spatial clusters by involving the cross product between the standardized value of a variable for feature *i* and that of the average of the neighboring values" (Ogneva-Himmelberger and Huang 2015). However, in order to determine the standardized value of a variable for a given feature, the mean value of the variable for the entire study area is calculated first (Anselin 1995). "Neighborhood", as conceptualized within the context of LISA, refers to the cells that the algorithm is defining as "neighbors". In order to define the "neighborhood", a spatial weight file must be defined and created.

A spatial weight affects results greatly because it determines which cells the tool will identify as "neighbors" (Anselin 2003). They can be constructed in two ways: either based on contiguity from polygon boundary files (how many cells away from the original the calculations are taking into consideration), or based on distance between polygons. For our analysis, we chose the first option, as our main interest lies in understanding how the nuances of crime and perception are affected at such a small scale as an individual neighborhood. GeoDa provides two types of spatially contiguous weights which are rook's (uses cells that touch the line boundaries of each cell) and queen's (similar to rook's, but includes cells

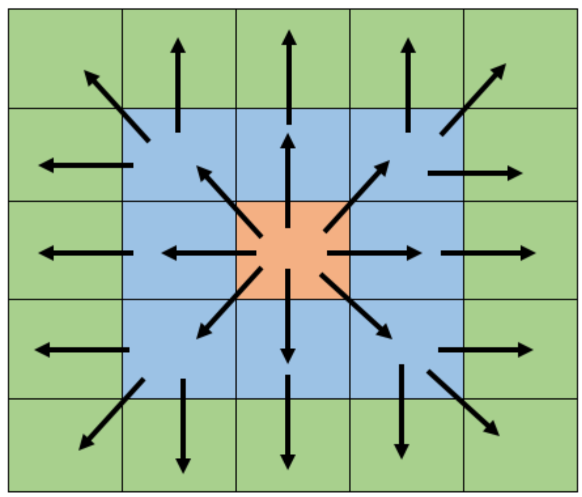


Figure 7. Example of what 2nd order queen spatial weight considers "neighbors". The orange cell in the middle represents the cell that the algorithm compares to its "neighbors". The blue cells immediately outside of the orange cell are the 1st-order queen (which includes corners of the cell) and the green cells on the outermost part of the "neighborhood" represent the 2nd order (the extent of the conceptualization of the "neighborhood" for the spatial weight).

that touch corners of cells as well). Another important factor that affects the weight file is the order of contiguity. This factor will determine how many neighbors of cells the tool will consider in its calculations. We chose 2^{nd} order queen's for our weights file in order to account for the varying sizes of areas that respondents chose to mark. Essentially, this means the tool will calculate spatial autocorrelation between the two variables from the cells immediately surrounding it, plus the cells immediately surrounding those cells (see Figure 7).

For our analysis, the two variables being compared are a) the frequency of reported crime points and b) the frequency of perception ellipses (see Appendix for maps of crime and perception aggregated to the grid cells). In each 100 x 100 ft. grid cell, they are clustered into these four categories: 1) where values of both variables are high, 2) values of both variables are low, 3) values of cells with crime counts are high, but frequency of polygons marked as safe or unsafe is low, or 4) values of cells with crime counts is low, but frequency of polygons marked as safe or unsafe is high.

For analysis of unsafe perceptions, the first two categories would indicate that perceived fear or lack thereof statistically correlates with high or low levels of crime respectively. The last two categories would indicate that there is a mismatch between perception of fear and where crime is being reported. In other words, people may be perceiving an area as unsafe where crime is not being reported or may not be perceiving an area as unsafe, even though there are high levels of crime located there.

However, for analysis of safe perceptions, these categories would point to a different observation. If a cell is labeled as “high perception - high crime”, this would indicate that people are perceiving a space as safe, yet high levels of crime are happening there. If a cell is labeled as “low perception - low crime”, this would indicate that there are low levels of crime in this area, however, people are not marking the space as safe. The last two categories would indicate that respondents are perceiving safety in their neighborhood more accurately. For example, if a cell is labeled as “high perception - low crime”, this would mean people are perceiving that space as safe and that there is low crime there. Alternately, if a cell is labeled as “low perception - high crime”, this would mean that very few people are marking a space as safe where crime is occurring at higher rates.

4. Results

The results of this study can be described most easily by identifying areas of medium to high crime density, clusters of perception observations, and bivariate clusters where crime and perception had a statistically significant relationship. In other words, these areas emerged throughout the analysis of results as spaces of interest because they appeared often, and from both the visual and spatial statistical analysis. The areas identified represent a variety of spaces, including businesses such as a fast food chain, a bar, a convenient store, a public school, a university, a public park, a youth center, a bus stop, three streets, and four street corners. Throughout the analysis, the areas will be referred to as:

1. **McDonald's**, on Main Street close to the far West side in the project area
2. **Moynihan's Pub**, on Main Street near the north east side in the project area
3. **Tedeschi,** on Main Street close to the far west side in the project area
4. **University Park Campus School** (UPCS), on Freeland Street near the West side of the project area
5. **Clark University**, officially located just outside the middle-North area of the project boundary, but some buildings span just West and East of it
6. **Royal Worcester Apartments**, on Grand Street between Main Street and Hollis Street
7. **Crystal or University Park**, large open space between Gates, Crystal, Illinois, and Main Streets in the mid-west portion of the project area
8. **The Boys and Girls Club**, located at the Southern end of Kilby and Gardner Streets in the southeast portion of the project area
9. **Bus Stop**, located in the middle of Main Street at the middle north boundary of the project area
10. **Streets**
    a. Crystal Street
    b. Wyman Street
    c. Kilby Street

11. **Corners** of

a. Gates/Illinois

b. Claremont/Main

c. Wyman/Main

d. Hammond/Main

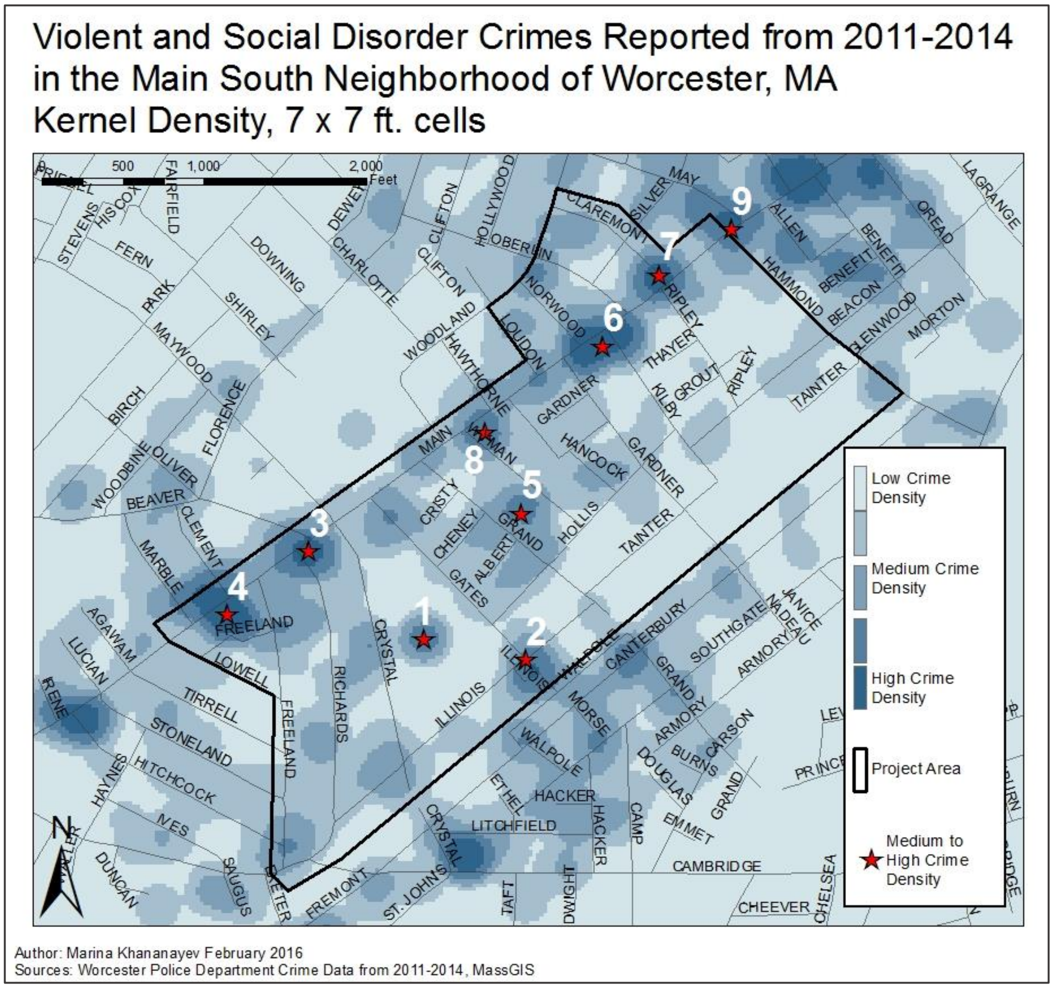


Figure 8. Map of crime density. Red stars indicate areas where a medium to high density of crime was found in our visual analysis of the results. Only areas inside or just outside of the study area were included.1. Crystal Park, 2. Gates/Illinois, 3. Tedeschi, 4. McDonald's, 5. Royal Worcester Apartments, 6. Moynihan's, 7. Claremont/Main, 8. Wyman/Main, 9. Hammond/Main

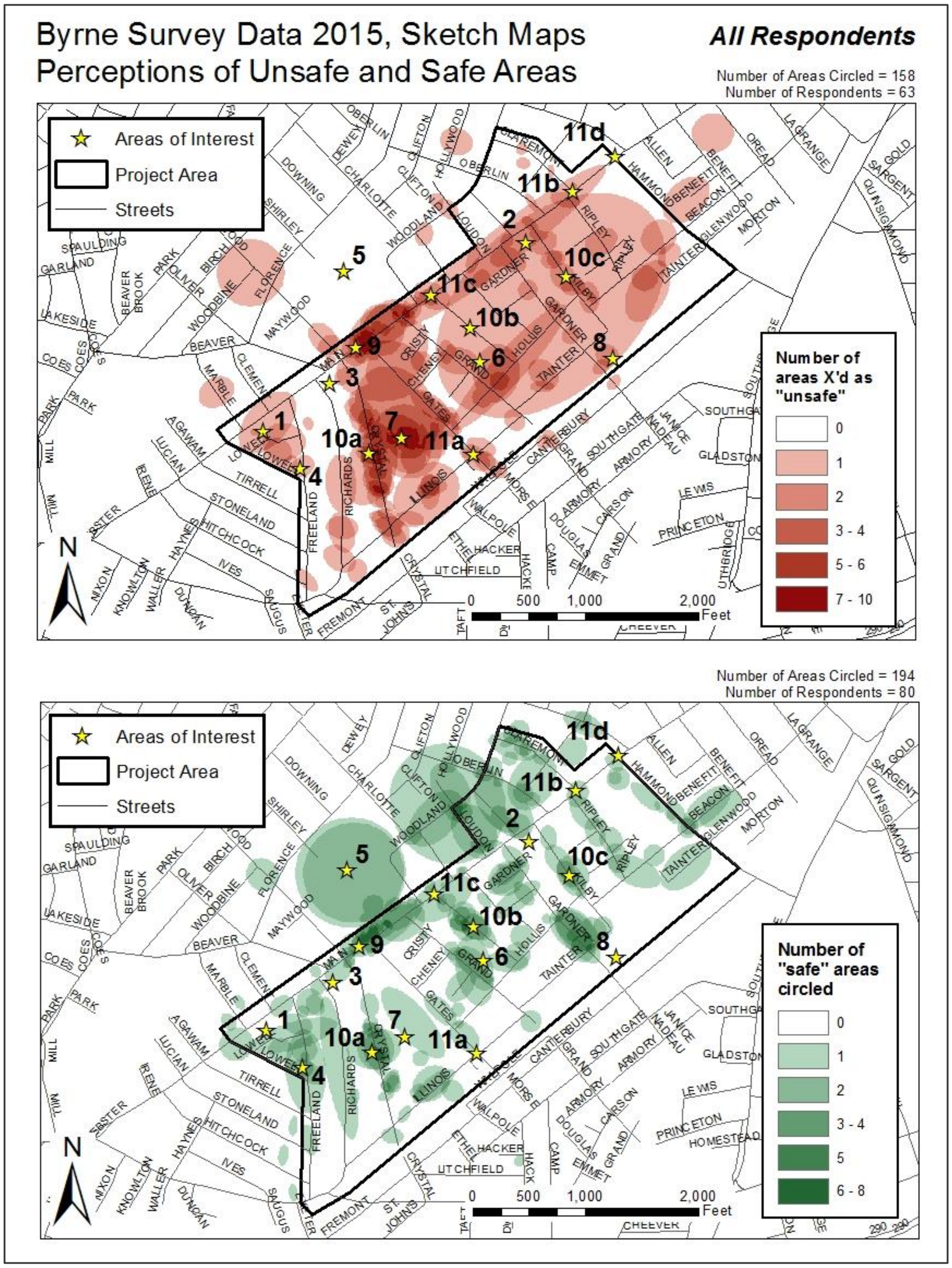


Figure 9. Sketch maps digitized to GIS. Yellow stars indicate areas where frequency of perceptions fell into the the top two classes of the range of data. 1. McDonald's, 2. Moynihan's, 3. Tedeschi, 4. UPCS, 5. Clark University, 6. Royal Worcester Apartments, 7. Crystal Park, 8. The Boys and Girls Club, 9. Bus Stop, 10a. Crystal Street, 10b. Wyman Street, 10c. Kilby Street, 11a. Gates/Illinois, 11b. Claremont/Main, 11c. Wyman/Main, 11d. Hammond/Main

Table 2. Summary of the areas of interest found from the analysis. Information about each location includes number of crimes within 100 ft. of that location, # of unsafe and safe responses attached to each location, and clusters from the Bivariate LISA analyses for safe and unsafe perceptions

Location	# of crimes that occurred within 100 ft.	# of "*unsafe*" responses	# of "*safe*" responses	Bivariate LISA: crime and *unsafe* areas	Bivariate LISA: crime and *safe* areas
1. McDonald's	31	2	0	Unsafe – High crime	Not Safe – High crime
2. Moynihan's Pub	29	0	1	Unsafe – High crime	Safe – High crime
3. Tedeschi	14	1	1	Not unsafe AND unsafe – High crime	Not safe AND safe – High crime
4. University Park Campus School	0	2	7	Not unsafe – Low crime	Safe – Low crime
5. Clark University	5	0	5	Not unsafe – Low crime	Safe – Low crime
6. Royal Worcester Apartments	24	2	2	Not significant	Not significant
7. Crystal Park	18	17	2	Unsafe – Low crime	Safe – Low crime (southern part)
8. Boys and Girls Club	0	3	9	Unsafe – Low crime	Safe – Low crime
9. Bus Stop	0	13	14	Not significant	Not significant
10a. Crystal Street	32	27	20	Not significant	Not significant
10b. Wyman Street	16	0	15	Not significant	Not significant
10c. Kilby Street	22	10	7	Not significant	Not significant
11a. Gates/Illinois	21	7	0	Not significant	Not significant
11b. Claremont/Main	26	2	1	Unsafe – High crime	Safe – High crime
11c. Wyman/Main	5	2	3	Unsafe – High crime	Safe – High crime
11d. Hammond/Main	19	0	1	Not Unsafe – High crime	Not Safe – High crime

1. McDonald's

Very few respondents marked any indication of feeling safe or unsafe in this area (see Figure 10). Despite little to no observations of safety recorded here, one of the highest crime density areas on the map can be found here (see Figure 8). 31 incidences of crime were reported from 2011-2014 within 100 ft. from the McDonald's on Main St.

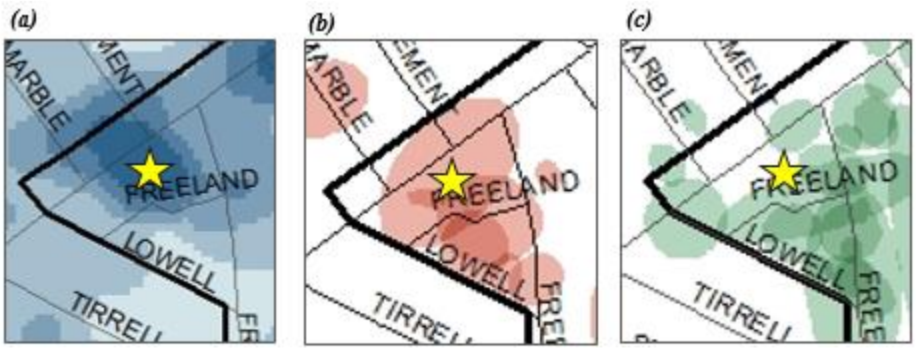


Figure 10. McDonald's on Main Street ***a)*** *Crime density,* ***b)*** *density of areas X'd as unsafe by all respondents,* ***c)*** *density of areas circled as safe by all respondents.*

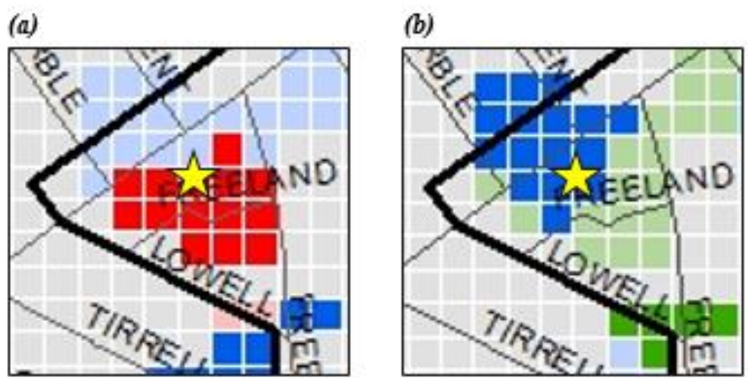


Figure 11. McDonald's on Main Street ***a)*** *perceived as unsafe - high crime (dark red),* ***b)*** *not perceived as safe – high crime (dark blue) AND perceived as safe – high crime (light green)*

The Bivariate LISA results show two clusters of statistically significant correlations between crime and perception at the McDonalds. According to Figure 11, the results show the area around McDonald's as an area that has clusters of high crime correlating with unsafe perceptions. When the Bivariate LISA tool was run to compare perceptions of safe areas with crime, results were more mixed and two types of clusters were identified. The analysis showed McDonald's as an area where a low number of safe areas correlated with high crime (see figure 11).

2. Moynihan's Pub

Similar to McDonald's, virtually no respondents marked Moynihan's as safe or unsafe. However, 69 incidences of crime were reported within 200 feet of this bar, which is located on Main Street (see Table 2). It is one of the darkest spots on the crime density map (see Figure 8).

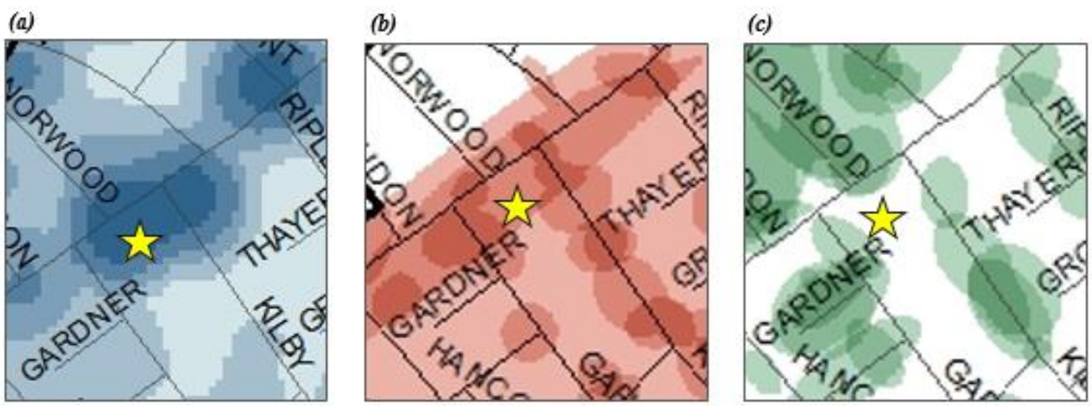


*Figure 12. Moynihan's Pub on Main Street **a)** Crime density, **b)** density of areas X'd as unsafe by all respondents, **c)** density of areas circled as safe by all respondents.*

According to the Bivariate LISA results, Moynihan's was an area where high crime correlated with a statistically significant number of areas marked as unsafe" (see Figure 13). According to the results that came from the Bivariate LISA analysis of "safe" perceptions, Moynihan's was perceived as safe which correlated with high levels of crime (see Figure 13).

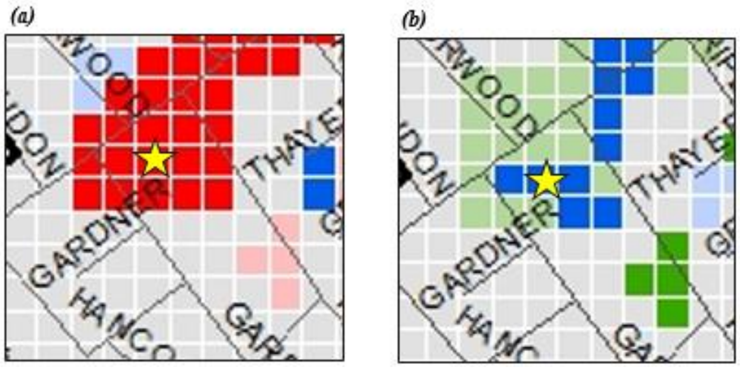


*Figure 13. Moynihan's Bivariate LISA results McDonald's on Main Street **a)** perceived as unsafe - high crime (dark red), **b)** not perceived as safe – high crime (dark blue)*

3. *Tedeschi*

Identified as one of the areas in the neighborhood with a high density of crime, little to no observations of safety perceptions were marked there (see Figure 14). One circle was marked by a respondent to indicate feelings of safety, and one X was marked to indicate unsafe feelings associated with this place on the map.

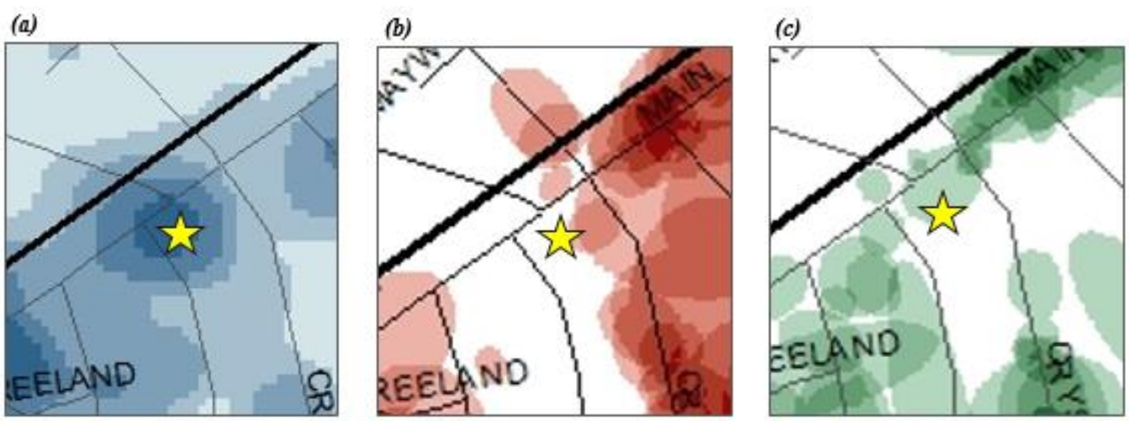


*Figure 14. Tedeschi Convenient Store **a)** Crime density, **b)** density of areas X'd as unsafe by all respondents, **c)** density of areas circled as safe by all respondents.*

The Bivariate LISA analysis shows mixed results. According to our results, the area is split in two with varying types of clusters (see Figure 15).

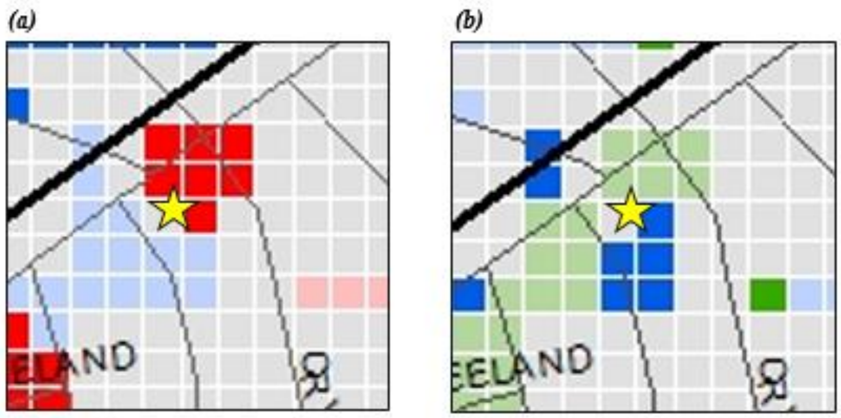


Figure 15. Tedeschi Bivariate LISA results a) perceived as unsafe - high crime (dark red) and not perceived as unsafe – high crime (light blue), b) not perceived as safe – high crime (dark blue) AND perceived as safe – high crime (light green)

4. UPCS

The area in and around the school was marked as safe only by respondents who had either lived in the neighborhood for 10+ years or were ages 14 to 24 years old (see Appendix for maps split by variable). However, very few respondents (n=2 ellipses) marked the area as unsafe (see Figure 16). UPCS was not identified as having a pattern of higher crime density compared to other areas in the neighborhood (see Figure 8). 0 crime incidences were reported within 100 feet of UPCS from 2011-2014 (see Table 2).

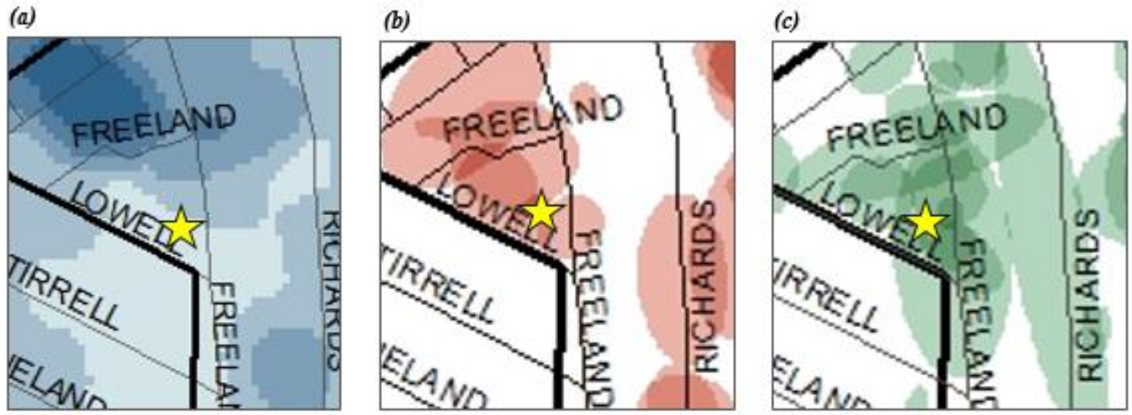


*Figure 16. University Park Campus School **a)** Crime density, **b)** density of areas X'd as unsafe by all respondents, **c)** density of areas circled as safe by all respondents.*

According to Bivariate LISA results, the area around UPCS shows mixed results for both safe and unsafe perceptions (see Figure 17).

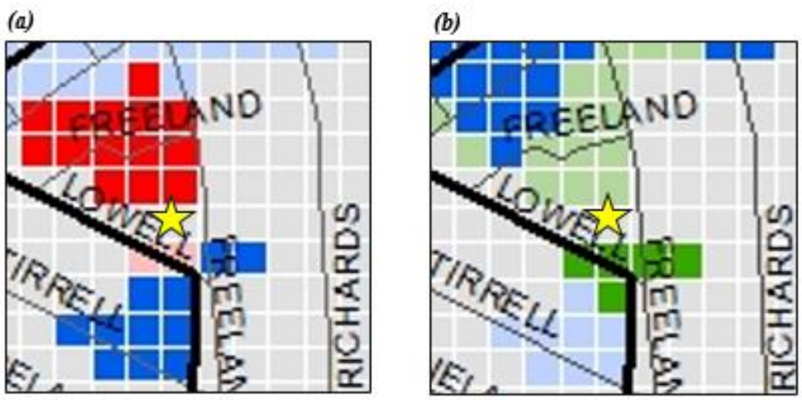


*Figure 17. University Park Campus School Bivariate LISA results **a)** perceived as unsafe - high crime (dark red) AND not perceived as unsafe – low crime (dark blue), **b)** perceived as safe – high crime (light green) AND perceived as safe – low crime (dark green)*

5. Clark University

Virtually no crime has been reported between 2011 and 2014 at Clark University (see Table 2). No respondents marked the campus as "unsafe". About 5 circles were placed there to indicate feelings of safety (see Figure 18). This did not differ much by demographic as there did not appear to be any group that overwhelmingly marked this area as safe compared to the other areas they circled on their maps.

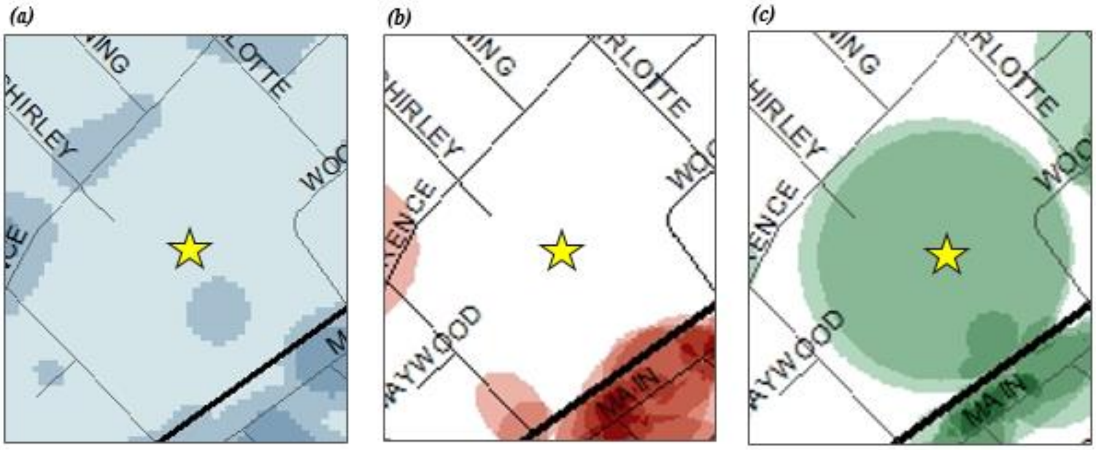


*Figure 18. Clark University **a)** Crime density, **b)** density of areas X'd as unsafe by all respondents, **c)** density of areas circled as safe by all respondents.*

Bivariate LISA results show Clark University as having a similar spatial pattern to the area around UPCS (see Figure 19). It is a place in the neighborhood with low crime, a high perception of safety, and a low number of unsafe perceptions.

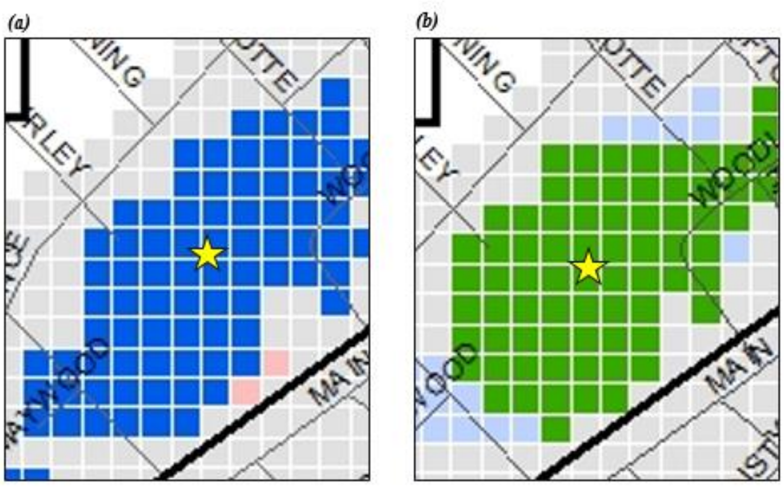


*Figure 19. Clark University Bivariate LISA results **a)** not perceived as unsafe – low crime (dark blue), **b)** perceived as safe – low crime (dark green)*

6. Royal Worcester Apartments

The large apartment complex on Grand Street is an area with a medium to high density of crime (23 incidences of crime reported within 200 feet of the building). According to Figure 20, a very small amount of respondents marked it as unsafe (n=3 X's), and a greater number marked it as safe (n=10 circles). The group of people who marked this area safe most times were women who have lived in the neighborhood for 4-10 years (see Appendix for maps split by variable).

Bivariate LISA results do not reveal this area to be a statistically significant cluster (see Appendix).

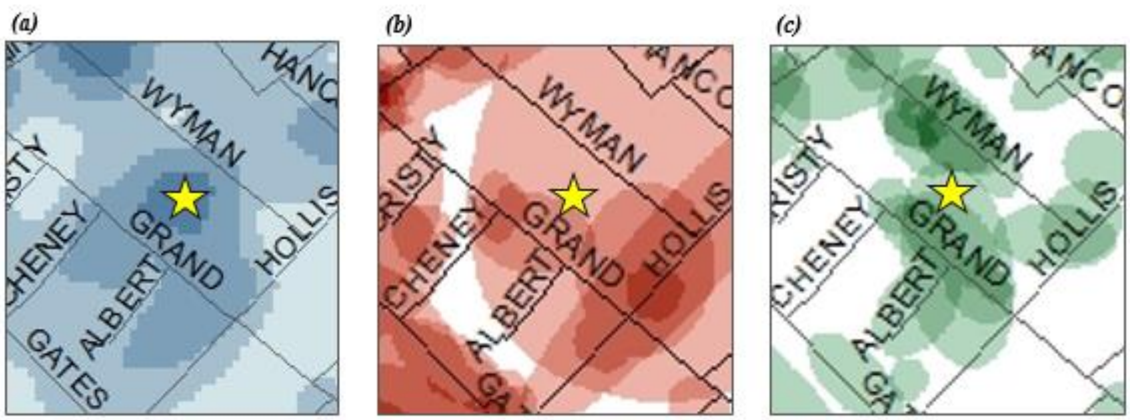


Figure 20. Royal Worcester Apartments ***a)*** *Crime density,* ***b)*** *density of areas X'd as unsafe by all respondents,* ***c)*** *density of areas circled as safe by all respondents.*

7. Crystal or University Park

Crystal Park is a medium density crime area in this neighborhood (18 incidences of reported crime in the park). On the sketch maps, it was marked as unsafe most frequently (see Table 2). When split by variable, some minor differences emerge from the sketch map results in Crystal Park. For example, out of every age category, the 14 to 24 year old respondents tended to have the most uniform and distinct perception of Crystal Park, with the highest frequency of unsafe perceptions occurring there (see Appendix for maps split by variable). It is interesting to note that when perceptions of Crystal Park are split by gender, females tended to leave Crystal Park blank more often when asked to mark both safe and unsafe areas (see Appendix for maps split by variable). Despite small spatial variations occurring throughout the maps, Crystal Park was rated as “unsafe” at a high frequency, even when disaggregated by gender, age, and length of residency (see Figure 21). No group of respondents marked Crystal Park as “safe” at a high frequency.

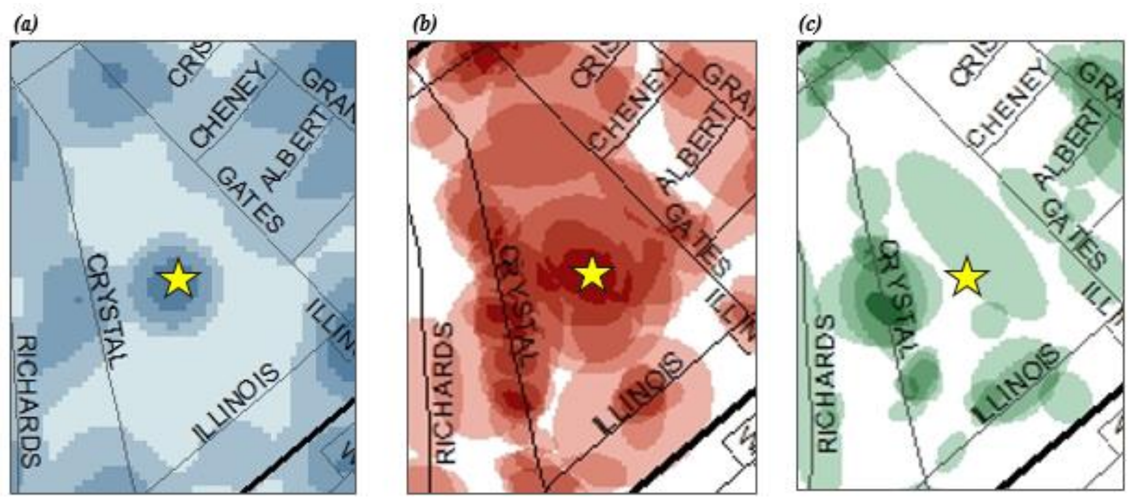


Figure 21. Crystal Park ***a)*** *Crime density,* ***b)*** *density of areas X'd as unsafe by all respondents,* ***c)*** *density of areas circled as safe by all respondents.*

The Bivariate LISA analysis results showed mixed results in Crystal Park. The majority of the park appears as statistically insignificant, despite the large number of unsafe perceptions recorded there. Of the cells that appear statistically significant, most are marked as areas that are perceived as unsafe and correlate with a low amount of crime (see Figure 22). The Bivariate LISA analysis run for correlations between safe areas and crime, reveals a correlation between places people perceived as safe with a low amount of crime.

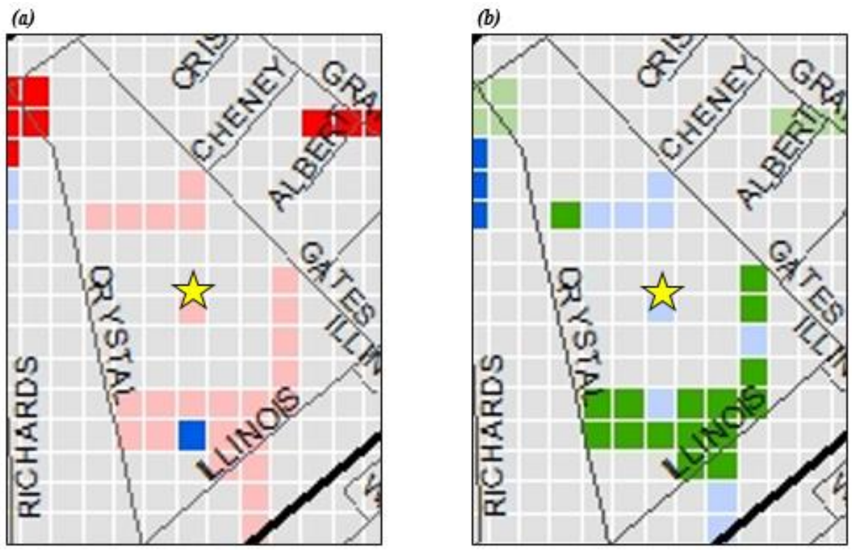


*Figure 22. Crystal Park Bivariate LISA results a) small amount of cells appear perceived as unsafe – low crime (light red), **b)** perceived as unsafe – low crime (light blue) AND perceived as safe – low crime in the southern portion of the park (dark green)*

8. The Boys and Girls Club

The area in and around the Boys and Girls Club emerged as an area where many circles indicating feelings of safety were marked (see Figure 23). 9 “safe” circles were marked around the Club, and only 3 “unsafe” X’s were marked here. The overwhelming majority of safe circles were marked by females (n=7), whereas males only marked 2 circles of safety in and around the Club. Little to no crime was reported here from 2011-2014 (see Appendix for maps split by variable).

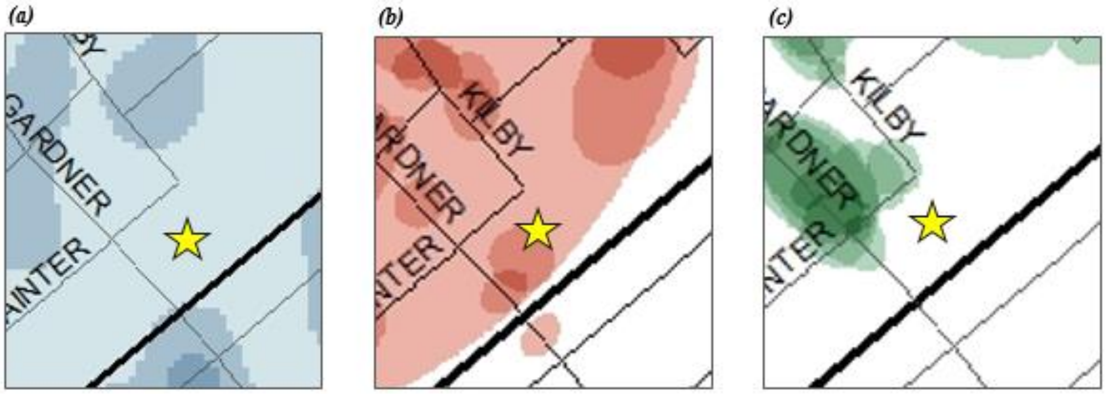


*Figure 23. The Boys and Girls Club **a)** Crime density, **b)** density of areas X'd as unsafe by all respondents, **c)** density of areas circled as safe by all respondents.*

When statistically analyzed with the Bivariate LISA tool, the Boys and Girls Club is an area of low crime that clusters with cells categorized as a high frequency of unsafe perceptions as well as safe perceptions (see Figure 24). Results indicate that the tool can statistically verify that there is a low amount of crime there, however, perceptions generate more conflicting results.

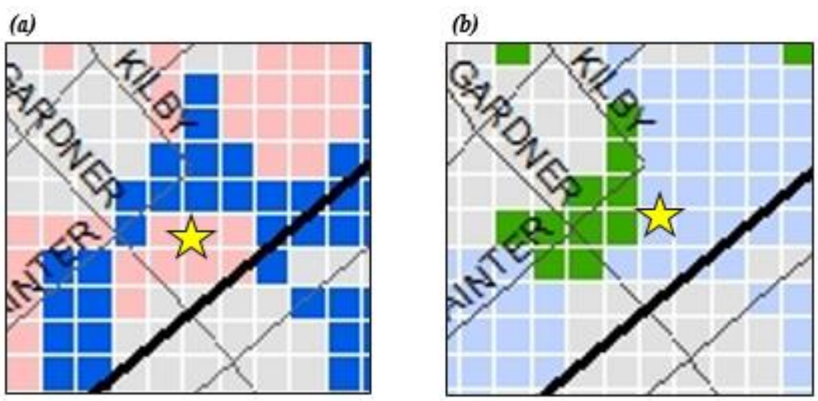


*Figure 24. The Boys and Girls Club Bivariate LISA results **a)** perceived as unsafe - low crime (light red) AND not perceived as unsafe – low crime (dark blue), **b)** not perceived as safe – low crime (light blue) AND perceived as safe – low crime (dark green)*

9. Bus Stop

The bus stop on Main Street was marked at a high rate as either safe or unsafe by all respondents. However, this area did not emerge as a medium or high crime density place on the map (see Figure 25). When split by demographic, the results show some variation in perception. For example, when split by length of residency, those who have lived in the neighborhood for less than 3 years indicated feeling unsafe at the bus stop, which those who have lived in the neighborhood for over 4 years indicated feeling safe there (see Appendix for maps split by variable). Females marked the area as unsafe, while males marked it as safe (see Appendix for maps split by variable). When split by age, perception did not differ in any spatial patterns (see Appendix for maps split by variable).

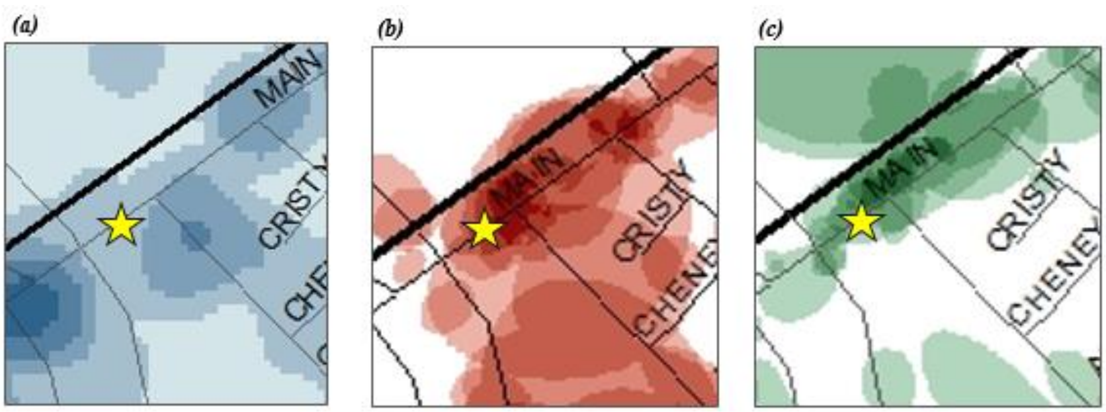


*Figure 25. Bus Stop on Main Street **a)** Crime density, **b)** density of areas X'd as unsafe by all respondents, **c)** density of areas circled as safe by all respondents.*

Bivariate LISA results do not reveal the bus stop as a statistically significant area, despite the high number of observations marked there on the sketch maps (see Figure 26).

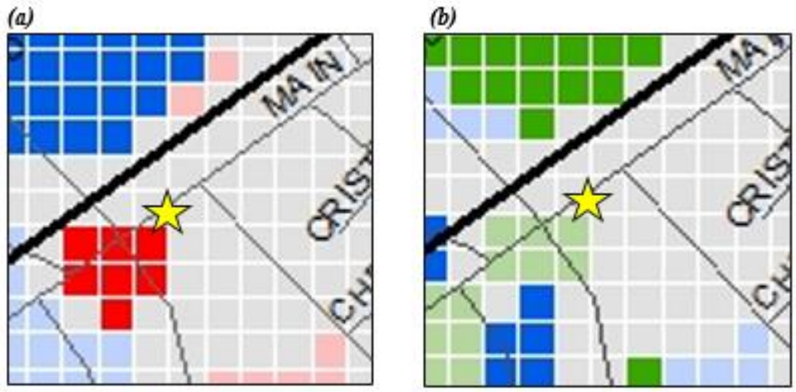


Figure 26. Bus Stop on Main Street Bivariate LISA results ***a)*** *not significant,* ***b)*** *not significant*

10. Wyman Street, Crystal Street, and Kilby Street

Wyman, Crystal, and Kilby were streets where varying amounts of reported crime occurred. For example, 16 incidences of crime have been reported on Wyman Street, 22 incidences of crime have been reported on Kilby Street, and 32 incidences of crime have been reported on Crystal Street. However, none of these streets appeared in the top ten highest crime density streets within 1,000 feet of the study area (see Table 3).

Of these three streets, Crystal Street and Kilby Street had the most disagreement amongst perception responses. For example, a significant number of both safe and unsafe responses were marked on both Crystal and Kilby (Figure 27). Kilby Street was marked as unsafe 10 times and circled as safe 6 times by all respondents while Crystal Street was marked as unsafe 20 times and circled as safe 19 times (see Figures 27 and 28). Perceptions of safety on Kilby Street did not differ when split by demographic.

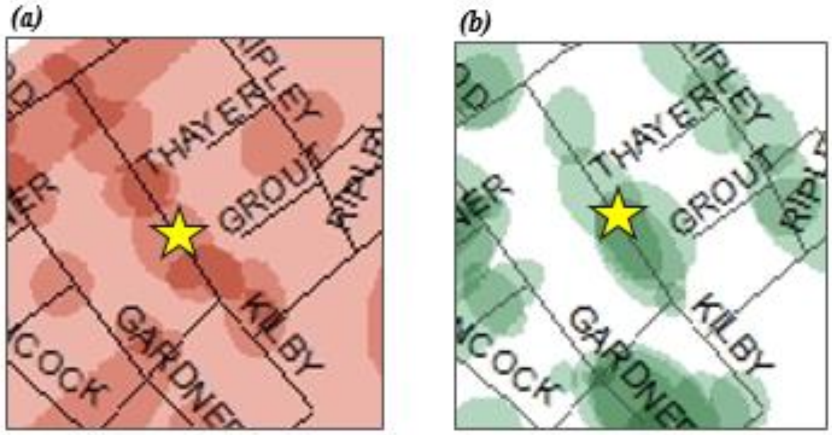


*Figure 27. Kilby Street **a)** density of areas X'd as unsafe by all respondents, **b)** density of areas circled as safe by all respondents.*

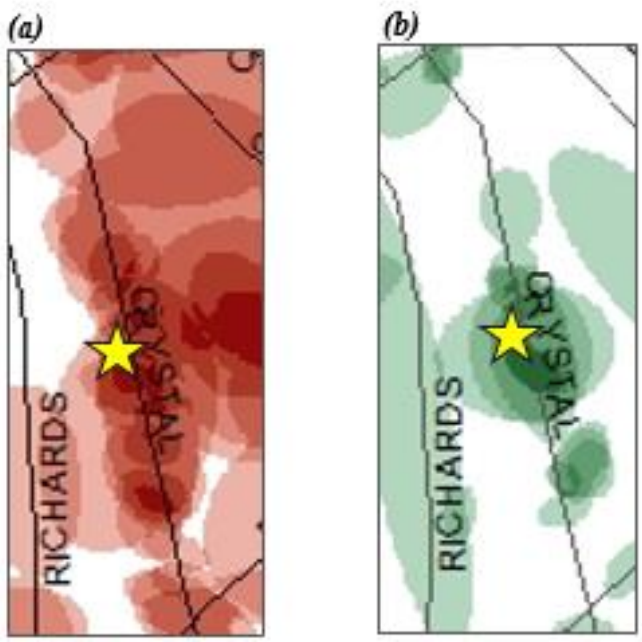


Figure 28. Crystal Street a) density of areas X'd as unsafe by all respondents, b) density of areas circled as safe by all respondents.

However, when perceptions were split by demographic on Crystal Street, some groups marked a significant number of both safe and unsafe spaces while others tended to agree more on how they felt about Crystal Street. For example, those who have lived in the neighborhood for less than 3 years and respondents ages 40+ recorded both a high number of safe and unsafe observations there (see Appendix for maps split by variable). Respondents ages 14 to 24 years old marked Crystal Street as safe 5 times. Older respondents (ages 25-40) marked it as unsafe 4 times. Females marked this street as "unsafe" 14 times whereas males marked Crystal Street as "safe" 10 times and "unsafe" only 1 time (See Appendix).

Table 3. Summary of streets with the highest amount of crime.

Reported Crime Incidences by Street,
Top Ten Highest Crime Density Streets

Street Name	**Number of crime incidences reported**
Main Street	450
Canterbury Street	102
Cambridge Street	93
May Street	65
Grand Street	61
Woodland Street	58
Oread Street	58
Richards Street	52
Southgate Street	49
Gates Street	48

Source: Worcester Police Department, Crime Incidences within 1,000 ft. of the Byrne project area from 2011-2014

Wyman Street was marked as "safe" consistently, even when split by demographic. 14 safe circles were drawn here by all respondents (see Figure 29). None of the respondents marked Wyman Street as unsafe (see Figure 29).

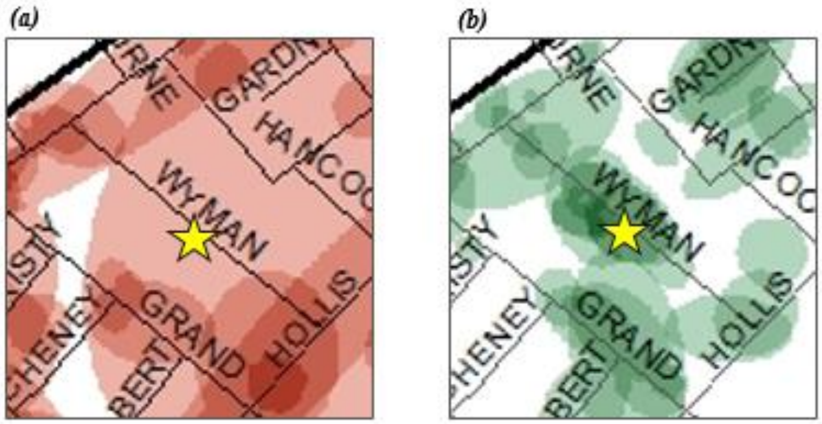


Figure 29. Wyman Street ***a)*** *density of areas X'd as unsafe by all respondents,* ***b)*** *density of areas circled as safe by all respondents.*

The Bivariate LISA results do not reveal any statistically significant results associated with areas along Crystal, Wyman, and Kilby streets. Clusters seem to be associated with areas surrounding the streets, but not along the streets themselves (see Figure 30).

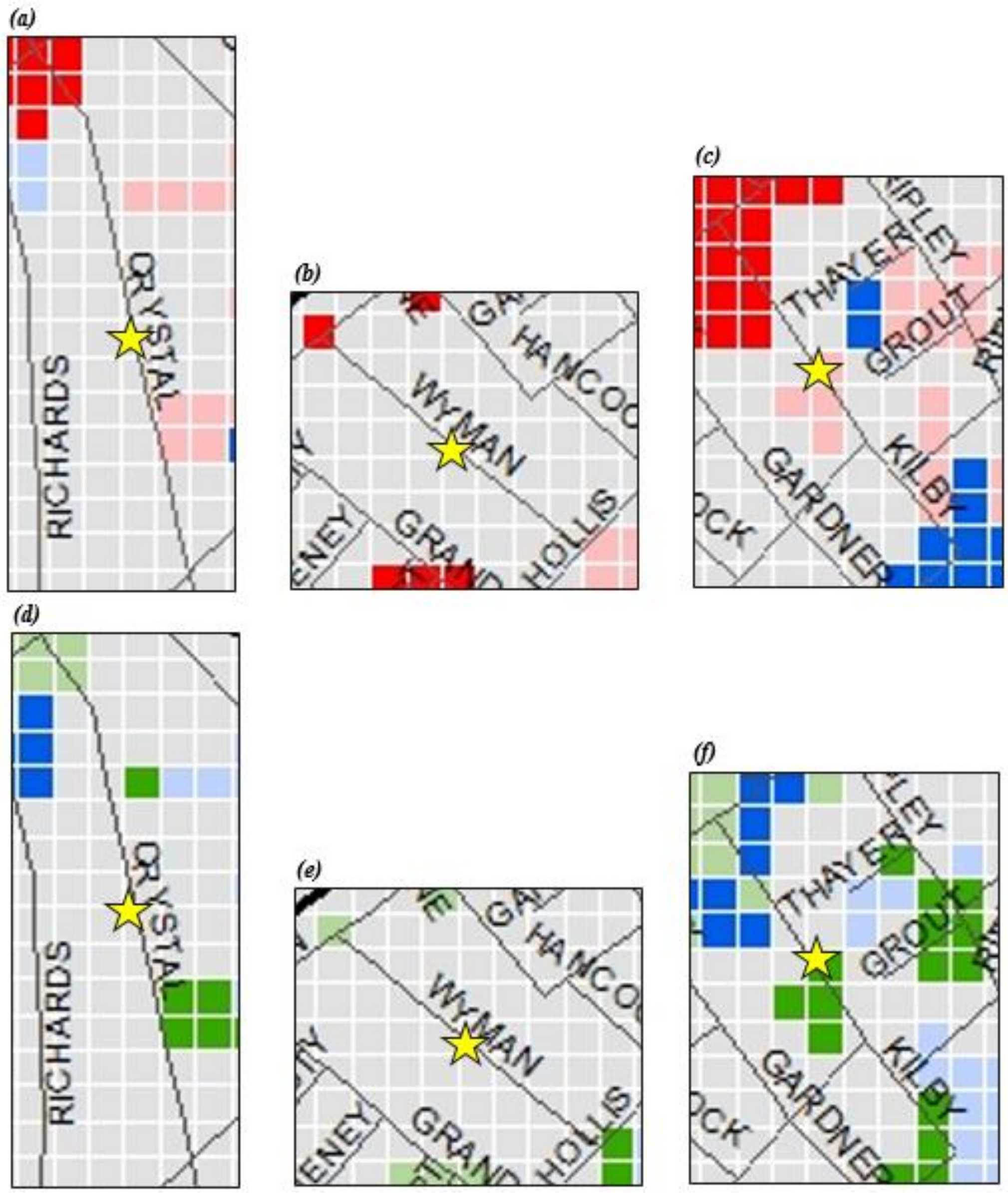


*Figure 30.Bivariate LISA results for Crystal, Wyman, and Kilby Streets **a)** and **d)** Crystal Street does not have any significant bivariate clusters **b)** and **e)** Wyman Street does not have any significant bivariate clusters **c)** and **f)** Kilby Street is mostly insignificant, aside from a few clusters in small sections on the street*

11. Corners of a) Gates/Illinois, b) Claremont/Main, c) Wyman/Main, and d) Hammond/Main

The corner of Gates and Illinois was both a high crime density area and an area where respondents indicated they felt unsafe at a high frequency. No respondents circled this area as safe, while 7 “unsafe” X’s were marked there (see Figure 31). When split by demographic, no significant difference was found amongst the respondents. Claremont and Main (see Figure 32), Wyman and Main (see Appendix), and Hammond and Main (see Appendix) were three street corners in and around the project area that had a high density of crime, yet little to no observations marked there by respondents.

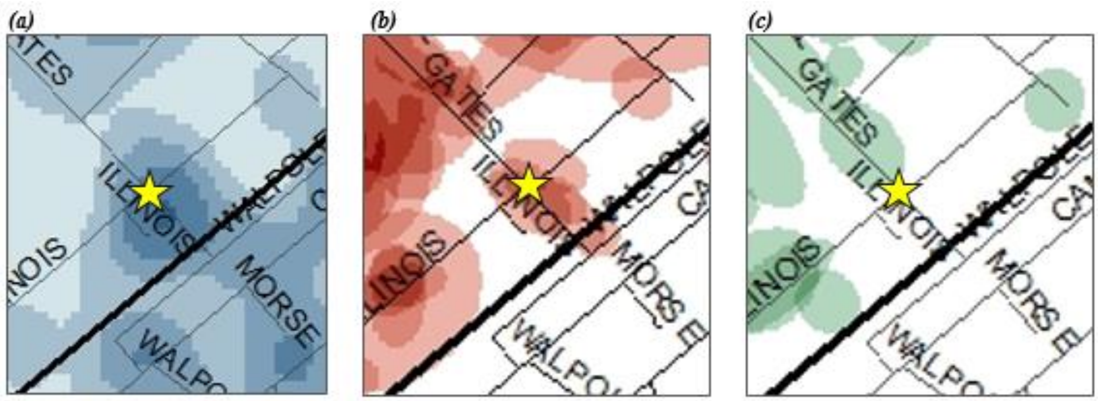


*Figure 31. Corner of Illinois and Gates **a)** Crime density, **b)** density of areas X'd as unsafe by all respondents, **c)** density of areas circled as safe by all respondents.*

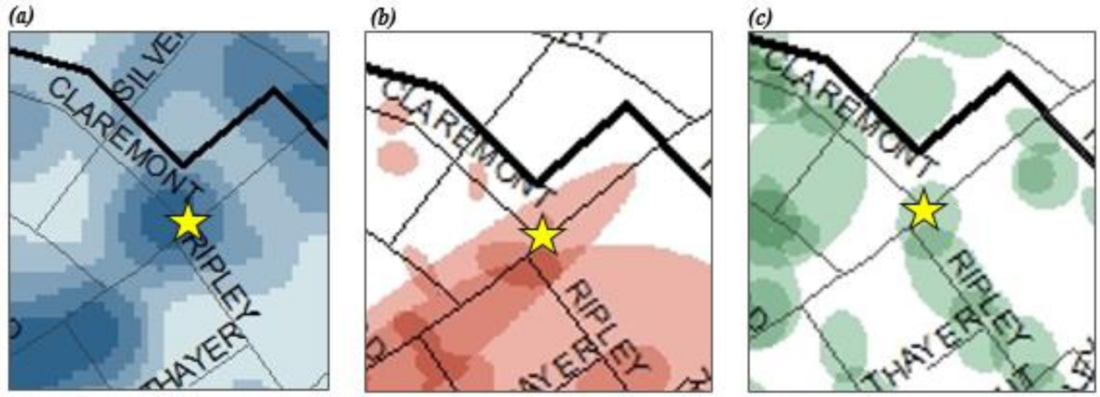


*Figure 32. Corner of Claremont and Main **a)** Crime density, **b)** density of areas X'd as unsafe by all respondents, **c)** density of areas circled as safe by all respondents.*

The Bivariate LISA results did not coincide with the visual analysis. At the corner of Illinois and Gates, the Bivariate LISA analysis produced cells marked as insignificant, despite the high pattern of crime observed there along with a high unsafe perception from the sketch maps (see Figure 31).

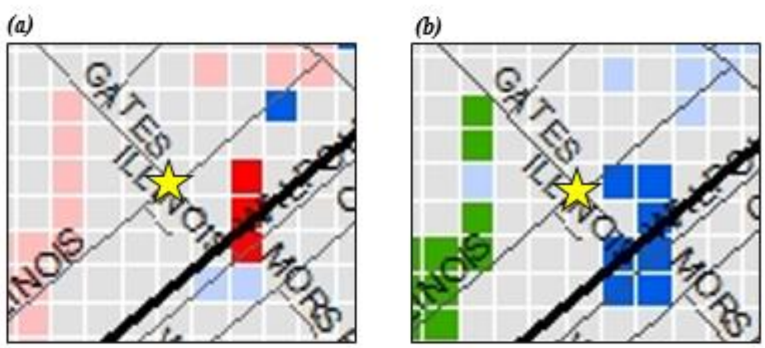


*Figure 33. Corner of Gates and Illinois Bivariate LISA results **a)** not significant, **b)** not significant*

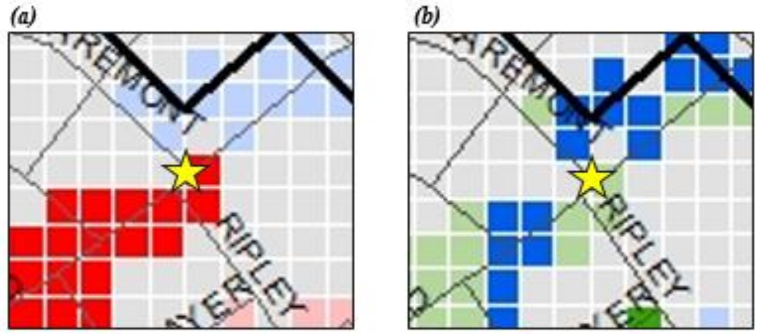


*Figure 34. Corner of Claremont and Main Bivariate LISA results **a)** perceived as unsafe - high crime (dark red), **b)** perceived as safe – high crime (light green)*

At Claremont and Main, results show a small cluster of cells that indicate a high number of “unsafe” and “safe” perceptions correlating with high crime, despite the insignificant number of observations that occurred there (see Figure 34). The last two corners in our analysis are areas where a pattern of high crime is correlated with an insignificant number of perception observations (see Appendix).

5. Discussion

Before discussing any of the results, following in line with Curtis et al.’s methods and placing importance on transparency, we will describe the serious limitations of this research project and how they may have skewed and affected the results (2014). These limitations can be described in two main categories: 1) the way the survey data was collected and 2) parameters for the Bivariate LISA analysis.

5.1 Limitations

First of all, because this data was collected as a part of a larger survey, less attention was given to the way the sketch maps were operationalized. The blank map itself spanned a significant area around the neighborhood surveyed, yet had an outline of the project area defined by the national grant that was received, rather than allowing respondents to define perceptions of their own neighborhood. This is problematic because some respondents seem to have marked outside the boundary of the project, while others tended to stay inside of it. While the respondents surveyed live within the project boundary lines, their perception may still be influenced by factors outside of those lines as well.

Secondly, respondents were not asked to indicate why they felt safe or unsafe in the areas they marked, which previous studies in line with this type of research have noted as one of the most important aspects to understanding sketch maps (Curtis et al. 2014). More qualitative data on the sketch maps would have created a more well-rounded and multi-faceted analysis of the phenomenon of fear in this neighborhood, potentially leading to a more informed and practical application of the data to achieve the goals of the Byrne project. In general, this research took somewhat of a top-down approach to analyzing the data. Community-based research could have proven to be useful in the analysis to interpret results and generate potential solutions to improving feelings of safety.

Another issue that may have skewed results is the number of observations that seem to be circled solely around the street names, indicating that people may be attaching their feelings of safety or unsafety with a street that they know the name of, rather than perceiving their environment on a smaller, more refined scale. Although this is an inherent problem with the sketch map method, due to the need to represent a space from a bird's eye view, researchers have very recently been coming up with more innovative ways to analyze perceptions of place that is more based in the reality of how people experience their neighborhoods every day. Promise lies in these methods, which measure fear of crime using innovative techniques such as hand-held GPS cellphone applications (Solymosi, Bowers, and Fujiyama 2015), measuring skin temperature responses in relation to place (Nold 2004), and simply transferring methods of hand-drawn techniques to Web-based mapping methods (Kohm 2009).

As can be seen in the results, there appears to be little similarities between the descriptive maps compared with the Bivariate LISA maps. Two questions arise: what may have caused this difference? And which results should be interpreted as "correct"? First off, this difference seems to be caused in part by the weight file chosen. As can be seen in the results, unsafe and safe areas are perceived on extremely varying scales. If an area, was marked as safe or unsafe many times and all of the observations were relatively small areas, the Bivariate LISA tool did not identify this as a cluster because, although these the values in these cells were statistically higher than most other cells, they did not span as far as the other clusters identified. This problem is difficult to mediate due to the way people marked their perceptions of safety. The area of spaces marked ranges from 2,940 sq. ft. (about the size of one side of a street corner) to

2,868,655 sq. ft. (about half of the Byrne project area). This can be seen most clearly as a problem for the area around the bus stop on Main Street. People marked this area frequently as both safe and unsafe, however, they used extremely small X's and O's to indicate these feelings. The weights file we chose compared cells that spanned farther than these perceptions were marked, resulting in a lack of statistically significant results for the bus stop.

This issue also occurred when analyzing perceptions that were marked on the street level. The weights file spans outward in a square shape of cells, which does not account for crime and perceptions that are found associated with streets.

5.2 Findings

Despite these limitations, a few important observations and implications can be drawn from the analysis. While results show some initial patterns about spatial variability of the sketch maps, only a few areas will be discussed in depth, as they represent spaces where most of the observations were made (or not made) and where high densities of crime appeared.

Crystal Park

While statistically comparing reported incidences of crime to perceptions of safety proved to be problematic in many ways, one can say that Crystal Park appears to be a space that is unanimously perceived as unsafe by all types of respondents included in this analysis. However, only 18 crimes were reported in Crystal Park from 2011 to 2014, a significantly lower number compared to other areas in the neighborhood. Without qualitative data on when and why residents feel unsafe there, it is hard to make any claims about causation. People may feel unsafe in Crystal Park for the following reasons: physical disorder (trash in the park, graffiti), previous victimization, or the presence or absence of people, to name a few. While results show that a spatial pattern begins to emerge in Crystal Park, the complex nature of perception mixed with the way the crime data is represented on the map as multiple points on one spot in Crystal Park make results difficult to interpret from the statistical method we chose.

Bus Stop on Main Street

This bus stop is frequented by many people all the time. The overlap of safe and unsafe perceptions here indicates once again that fear is complex and may depend on the individual. Some people may associate a large number of people with feelings of security, while others may associate feeling unsafe when there are many people occupying an area. Results from this study show that gender may play a role in this perception, as males marked the bus stop as safe, while females actively marked it as unsafe. This area did not emerge as a place with a high density of crime, indicating that the presence of crime does not play a role in the perceptions of safety at the bus stop.

Businesses: McDonald's and Moynihan's Pub

These two fairly well-known spaces in the neighborhood were not marked by a significant number of respondents, however the Bivariate LISA analysis showed these areas had a statistically significant relationship between spaces marked as safe and unsafe with a high amount of crime. This may have been influenced by the areas respondents circled that were close to the two businesses, which would have been captured by the weight file we chose. Because we are analyzing crime and perceptions at such a small scale of the Crystal Park neighborhood, the way that people marked their perceptions of safety may appear very close together. Clearly, the Bivariate LISA tool was not successful here at identifying that very few people marked this area on the map as an area that either made them feel safe or unsafe. Visual analysis shows a more accurate depiction of these areas and deserves further investigation as to why people did not perceive these spaces as safe or unsafe.

Crystal Street

While Crystal Street did not emerge from the Bivariate LISA results, it is interesting to note just how many responses were marked here in addition to the amount of crime reported on this street from 2011-2014. Out of all of the areas of interest that emerged from the results, Crystal Street had the highest amount of crime (32 crimes) as well as being the most frequently marked area (both safe and unsafe). Clearly, there seems to be a relationship here between crime and perceptions of safety. According to our results, females perceive Crystal Street as "unsafe" at a higher frequency than males, indicating the correlation between crime and unsafe perceptions is stronger for female respondents.

5.3 Conclusions and Further Study

As outsiders of the neighborhood, the researchers attempted to measure the relationship between reported incidences of crime and perceptions of safety. Although initial visual descriptions of the data collected indicate that perceptions of safety are somewhat misaligned with reported incidences of crime for some areas and correlated with others, results showed that the nature of this relationship is far too complex to be analyzed without further collection of data and a more robust method. It can be concluded that the Bivariate LISA tool is inadequate to measure the statistical relationship between perceptions of safety and crime, due to the varying nature of subjective perceptions that occur at scales such as street-level, street corner level, or perceptions associated with large parks such as Crystal Park. The scale at which perceptions were analyzed must also be considered in future studies. As stated in the discussion section, because people were marking areas at such varying scales and so close together, the Bivariate LISA tool showed certain areas, such as McDonald’s and Moynihan’s as places where people indicated feelings about their safety, even when visual analysis revealed that these areas were left blank by most respondents.

According to our results, the weight file and cell size played a huge role in the analysis. Future researchers must experiment with different weights files and look into a potentially more robust way to define the size and shape of cells or polygons used in the analysis. Additionally, many studies that employ the LISA tool in their analyses use polygons that reflect neighborhood boundaries or other boundaries that are more based in the realities of the people who live there. At the neighborhood scale, it can be difficult to capture these nuanced spaces, especially because from our results, we can see that they vary by scale and shape. However, a collaborative approach of asking people to draw significant areas within their neighborhood and help create the map that they would mark their perceptions on would truly create a participatory GIS approach and make interpreting results far more robust and useful. New methods for this are being developed as technological advancement progresses (Kim, Vasardani, and Winter 2016).

Given the restraints that most community development practitioners face when carrying out research and implementing strategies, some more advanced techniques mentioned above may be difficult to employ. If the researchers are to engage with a similar, but improved method in the future, a few changes may be made to the data collection process. First of all, it would be beneficial to remove the lines that bound the Byrne project area. From our results, we noticed that a few people marked areas outside the project area, indicating that perceptions of safety may span farther than the designated area. By giving people a map more free of markings, bias will be reduced and respondents can mark the area more freely. Additionally, a technique mentioned above in the literature review called “avoidance mapping” holds promise for researchers looking to analyze how fear is actualized in behavior, potentially leading to results that may inform implementation in a more practical way (Nasar et al. 1993; Nasar and Jones 1997; Doran and Lees 2005; Dennis 2006). Since avoidance behavior is central to many of the negative consequences associated with neighborhood vitality, measures that examine avoidance are relevant to the study of fear of crime.

In addition to a more collaborative approach to develop survey methods, more data in the form of focus groups to interpret initial findings post-survey would generate a clearer understanding about the relationship between crime and perception in this neighborhood. Not only would this improve the interpretation of results, but it would also foster a mutually beneficial relationship between the research partner and the community.

The research carried out sought to measure the relationship between the objective and subjective. It was done so in a way that incorporated little involvement from the community to design the survey and interpret results, leading to inconsistent and conflicting results. Despite these very serious issues with the research design, implementation, and interpretation, emerging patterns from the visual analysis reveal that high crime areas such as McDonald's and Moynihan's were not perceived as areas where people felt safe or unsafe. Was this due to the design of the blank map given to respondents that did not point out businesses or landmarks? Could it be that people simply do not attach any sort of emotion to these spaces? Additionally, Crystal Park and the bus stop on Main Street may also be further areas of interest for the research partner to examine, as a very relatively low amount of reported crime occurred there with a significant number of responses marked there indicating varying feelings of safety.

Our original questions sought to ask if reports of crime correlated to where residents felt safe or unsafe and if those perceptions changed the correlation when disaggregated by gender, age, or length of residency. Yes, some locations indicated that people feeling unsafe correlated with reported crime. However, with the data that was collected, the majority of areas analyzed showed that crime did not correlate with perceptions of safety and often even had conflicting results. Due to the small amount of variation amongst responses when split by age, gender, and length of residency, little could be determined about the relationship between respondent characteristic and their perceptions of crime. Future studies may want to disaggregate the data even further, especially when examining gender. Initial findings from this study suggest that gender plays a role in how people perceive crime, however, we are unsure of how the intersections of income or race might affect perceptions of safety in this neighborhood.

Without asking people why they marked these areas, any sort of correlation would be difficult to interpret and explain. The researchers must remain critical in their methods and involve the community to make any claims about the relationship between reported crime and perceptions of safety. The geography of fear is complex and must continue to be studied, as it has incredibly practical applications for community development. Yet, researchers must take the difficult, yet radical and essential approach to understanding this complex phenomena directly from the people who experience these realities on a daily basis.

Literature Cited

Anselin, Luc. "GeoDa™ 0.9 user's guide." *Urbana* 51 (2003): 61801.

Anselin, Luc. "Local indicators of spatial association—LISA." *Geographical analysis* 27.2 (1995): 93-115.

Anselin, Luc, Ibnu Syabri, and Youngihn Kho. "GeoDa: an introduction to spatial data analysis." *Geographical analysis* 38.1 (2006): 5-22.

Boschmann, E. Eric, and Emily Cubbon. "Sketch maps and qualitative GIS: using cartographies of individual spatial narratives in geographic research." *The Professional Geographer* 66.2 (2014): 236-248.

Breetzke, Gregory D., and Amber L. Pearson. "The fear factor: Examining the spatial variability of recorded crime on the fear of crime." *Applied Geography* 46 (2014): 45-52.

Brownlow, Alec. "A geography of men's fear." *Geoforum* 36.5 (2005): 581-592.

Burgess, Jacquelin A. "Place-making: the contribution of environmental perception studies in planning." *Geography* (1979): 317-326.

Ceccato, Vania A., and Folke Snickars. "Adapting GIS technology to the needs of local planning." *Environment and planning B: Planning and design* 27.6 (2000): 923-937.

Clemente, Frank, and Michael B. Kleiman. "Fear of crime in the United States: A multivariate analysis." *Social forces* 56.2 (1977): 519-531.

Chainey, S. P. "Examining the influence of cell size and bandwidth size on kernel density estimation crime hotspot maps for predicting spatial patterns of crime." *Bulletin of the Geographical Society of Liege* 60 (2013): 7-19.

Chainey, S.P. and Ratcliffe, J.H. (2005) GIS and Crime Mapping. London: Wiley.

Chainey, S.P., Reid, S. and Stuart, N. (2002) When is a Hotspot a Hotspot? A Procedure for Creating Statistically Robust Hotspot Maps of Crime. In Higgs, G. (ed.) Innovations in GIS 9 Socio-economic Applications of Geographic Information Science. London: Taylor & Francis.

Curtis, Jacqueline W., et al. "The prospects and problems of integrating sketch maps with geographic information systems to understand environmental perception: A case study of mapping youth fear in Los Angeles gang neighborhoods." *Environment and Planning B: Planning and Design* 41.2 (2014): 251-71.

Dennis, Samuel F. "Prospects for qualitative GIS at the intersection of youth development and participatory urban planning." *Environment and Planning A* 38.11 (2006): 2039-2054.

Doran, Bruce J., and Brian G. Lees. "Investigating the spatiotemporal links between disorder, crime, and the fear of crime." *The Professional Geographer* 57.1 (2005): 1-12.

Doran, Bruce J., and Melissa B. Burgess. *Putting fear of crime on the map: Investigating perceptions of crime using geographic information systems*. Springer Science & Business Media, 2011.

Eck, J.E., Chainey, S.P., Cameron, J.G., Leitner, M. and Wilson, R.E. (2005) Mapping Crime: Understanding Hot Spots. USA: National Institute of Justice. Available online at http://www.ojp.usdoj.gov/nij.

Hirtle, Stephen C., and John Jonides. "Evidence of hierarchies in cognitive maps." *Memory & cognition* 13.3 (1985): 208-217.

Ferguson, Kristin M., and Charles H. Mindel. "Modeling fear of crime in Dallas neighborhoods a test of social capital theory." *Crime & Delinquency*53.2 (2007): 322-349.

Ferraro, Kenneth F. *Fear of crime: Interpreting victimization risk*. SUNY press, 1995.

Forrest, Ray, and Ade Kearns. "Social cohesion, social capital and the neighbourhood." *Urban studies* 38.12 (2001): 2125-2143.

Hunter, Albert, and Terry L. Baumer. "Street Traffic, Social Integration, and Fear of Crime*." *Sociological Inquiry* 52.2 (1982): 122-131.

Jackson, Jonathan. "Revisiting risk sensitivity in the fear of crime." *Journal of Research in Crime and Delinquency* 48.4 (2011): 513-537.

Kanan, James W., and Matthew V. Pruitt. "Modeling fear of crime and perceived victimization risk: The (in) significance of neighborhood integration." *Sociological inquiry* 72.4 (2002): 527-548.

Kasarda, John D., and Morris Janowitz. "Community attachment in mass society." *American sociological review* (1974): 328-339.

Kim, Junchul, Maria Vasardani, and Stephan Winter. "From descriptions to depictions: A dynamic sketch map drawing strategy." *Spatial Cognition & Computation* 16.1 (2016): 29-53.

King, Brian H. "Towards a participatory GIS: evaluating case studies of participatory rural appraisal and GIS in the developing world." *Cartography and geographic information science* 29.1 (2002): 43-52.

Kohm, Steven A. "Spatial dimensions of fear in a high-crime community: Fear of crime or fear of disorder? 1." Canadian Journal of Criminology and Criminal Justice 51.1 (2009): 1-30.

Ladd, Florence C. "Black Youths View Their Environment:" Neighborhood Maps"." *Environment and Behavior* 2.1 (1970): 74.

LaGrange, Randy L., and Kenneth F. Ferraro. "Assessing age and gender differences in perceived risk and fear of crime*." *Criminology* 27.4 (1989): 697-720.

López, Natalie, and Chris Lukinbeal. "Comparing police and residents' perceptions of crime in a phoenix neighborhood using mental maps in GIS." *Yearbook of the Association of Pacific Coast Geographers* 72.1 (2010): 33-55.

Matei, Sorin, Sandra J. Ball-Rokeach, and Jack Linchuan Qiu. "Fear and misperception of Los Angeles urban space a spatial-statistical study of communication-shaped mental maps." *Communication Research* 28.4 (2001): 429-463.

McGuire, P.G. and Williamson, D. (1999) Mapping Tools for Management and Accountability. Paper presented to the *Third International Crime Mapping Research Center Conference*, Orlando, Florida, 11–14 December 1999.

McMillan, David W., and David M. Chavis. "Sense of community: A definition and theory." *Journal of community psychology* 14.1 (1986): 6-23.

Nasar, Jack L. *The evaluative image of the city*. Thousand Oaks, CA: Sage Publications, 1998.

Nasar, Jack L., Bonnie Fisher, and Margaret Grannis. "Proximate physical cues to fear of crime." *Landscape and urban planning* 26.1 (1993): 161-178.

Nasar, Jack L., and Kym M. Jones. "Landscapes of fear and stress." *Environment and behavior* 29.3 (1997): 291-323.

Ogneva-Himmelberger, Yelena, and Liyao Huang. "Spatial distribution of unconventional gas wells and human populations in the Marcellus Shale in the United States: vulnerability analysis." *Applied Geography* 60 (2015): 165-174.

Pearsall, Hamil, et al. "Exploring youth socio-spatial perceptions of higher education landscapes through sketch maps." *Journal of Geography in Higher Education* 39.1 (2015): 111-130.

Perkins, Douglas D., John W. Meeks, and Ralph B. Taylor. "The physical environment of street blocks and resident perceptions of crime and disorder: Implications for theory and measurement." *Journal of environmental psychology* 12.1 (1992): 21-34.

Ratcliffe, Jerry H., and Michael J. McCullagh. "Chasing ghosts? Police perception of high crime areas." *British Journal of Criminology* 41.2 (2001): 330-341.

Scarborough, Brittney K., et al. "Assessing the relationship between individual characteristics, neighborhood context, and fear of crime." *Journal of Criminal Justice* 38.4 (2010): 819-826.

Solymosi, Reka, Kate Bowers, and Taku Fujiyama. "Mapping fear of crime as a context-dependent everyday experience that varies in space and time." *Legal and Criminological Psychology* 20.2 (2015): 193-211.

Taylor, Ralph B., Stephen D. Gottfredson, and Sidney Brower. "Block crime and fear: Defensible space, local social ties, and territorial functioning."*Journal of research in crime and delinquency* 21.4 (1984): 303-331.

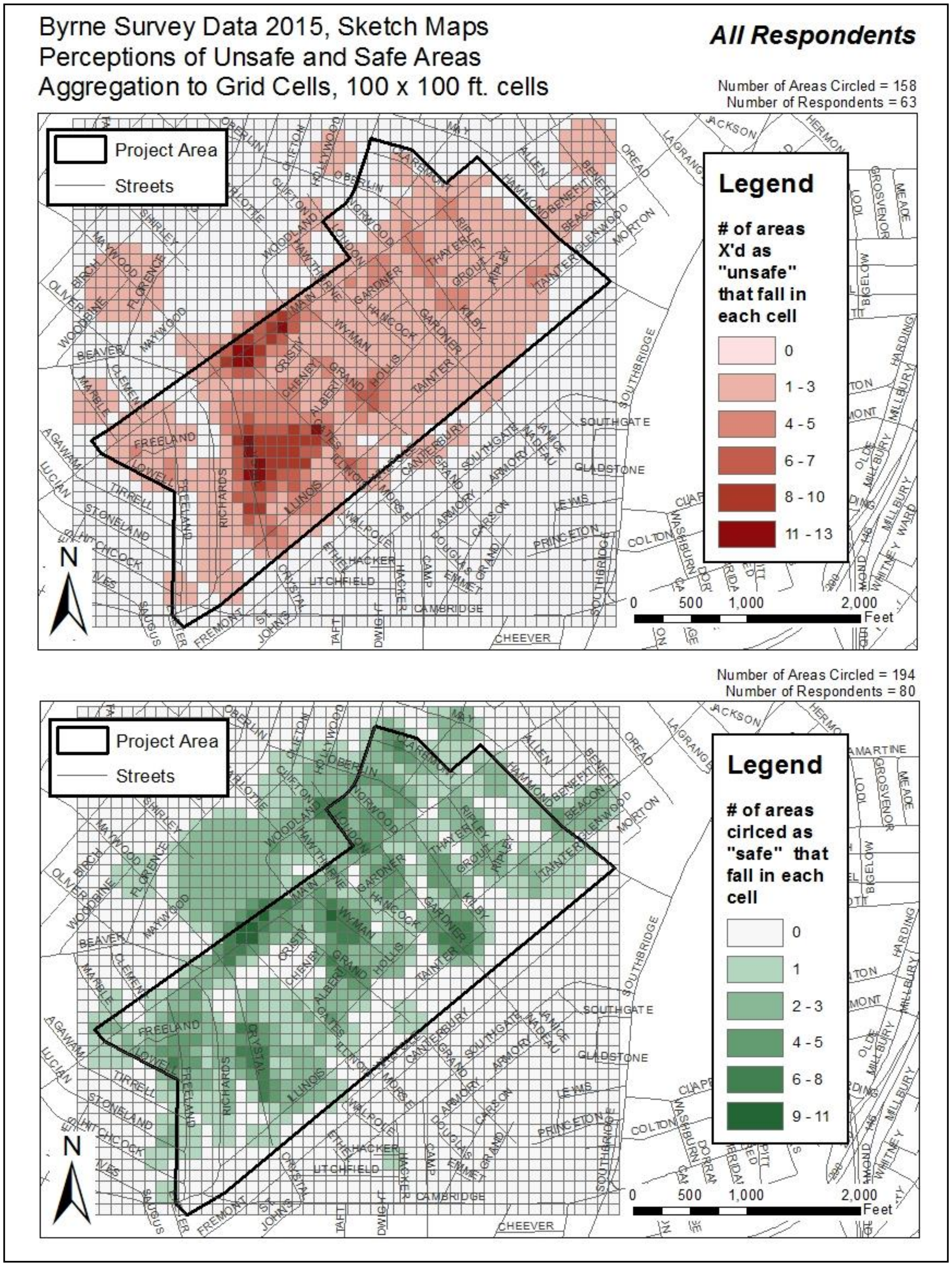
Warr, Mark. "Fear of crime in the United States: Avenues for research and policy." *Criminal justice* 4.4 (2000): 451-489.

Williamson, D., McLafferty, S., McGuire, P., Goldsmith, V and Mollenkopf, J (1999) A Better Method to Smooth Crime Incidence Data. ArcUser Magazine, January–March, 1999 1–5. Available online at http://www.esri.com/news/arcuser/0199/crimedata.html.

Williamson, D., McLafferty, S., McGuire, P., Ross, T., Mollenkopf, J., Goldsmith, V and Quinn, S (2001) Tools in the Spatial Analysis of Crime. In Hirschfield, A. and Bowers, K. (eds) Mapping and Analysing Crime Data: Lessons from Research and Practice. London: Taylor & Francis, pp 187–202.

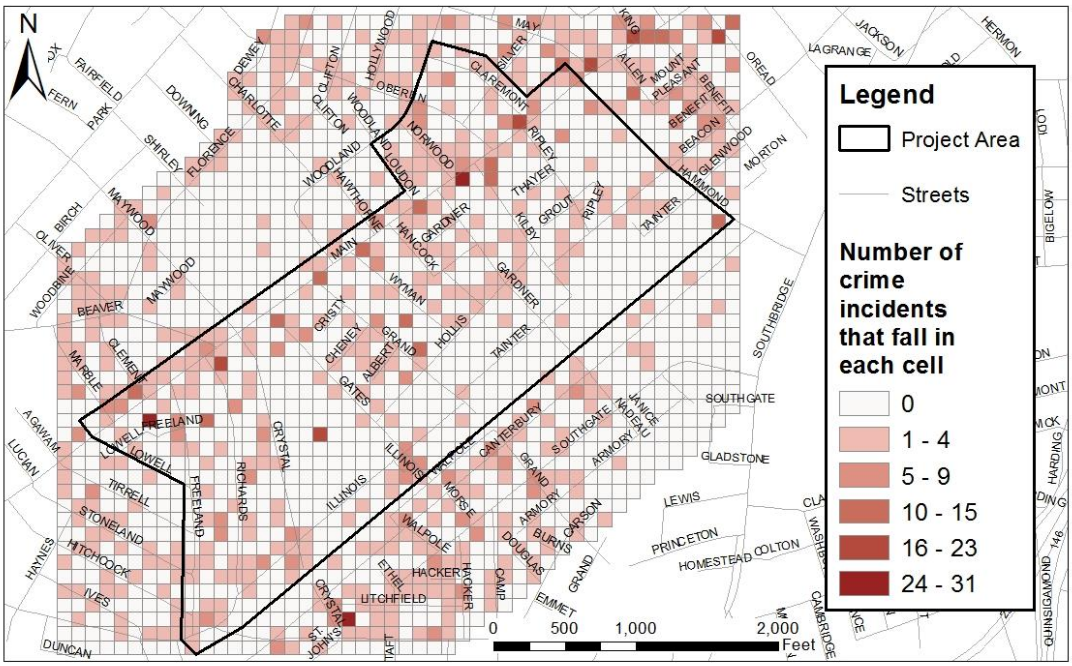
Wilson, Ronald E., Timothy H. Brown, and Beth Schuster. "Preventing neighborhood crime: Geography matters." *NIJ Journal* 263 (2009): 30-35.

Appendix.



Byrne Survey Data 2015, Sketch Maps
Perceptions of Unsafe and Safe Areas
Aggregation to Grid Cells, 100 x 100 ft. cells
All Respondents
Number of Areas Circled = 158
Number of Respondents = 63
Project Area
Streets
Legend
# of areas X'd as "unsafe" that fall in each cell
0
1 - 3
4 - 5
6 - 7
8 - 10
11 - 13
N
0 500 1,000 2,000 Feet
Number of Areas Circled = 194
Number of Respondents = 80
Project Area
Streets
Legend
# of areas cirlced as "safe" that fall in each cell
0
1
2 - 3
4 - 5
6 - 8
9 - 11
N
0 500 1,000 2,000 Feet

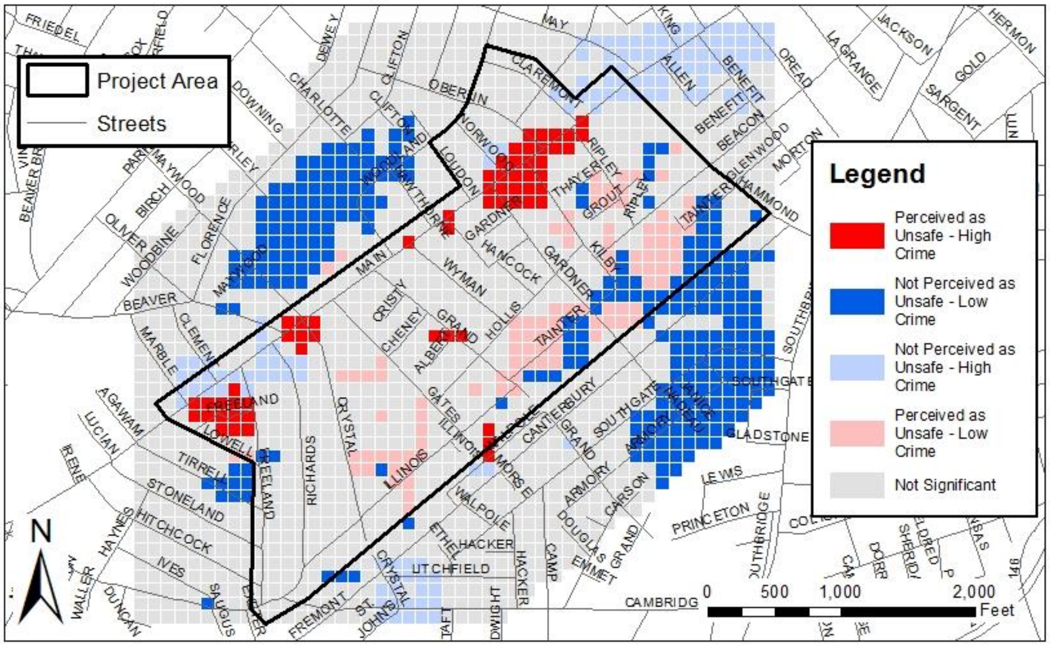
Violent and Social Disorder Crimes Reported from 2011-2014
in the Main South Neighborhood of Worcester, MA
Aggregation to Grid Cells, 100 x 100 ft. cells

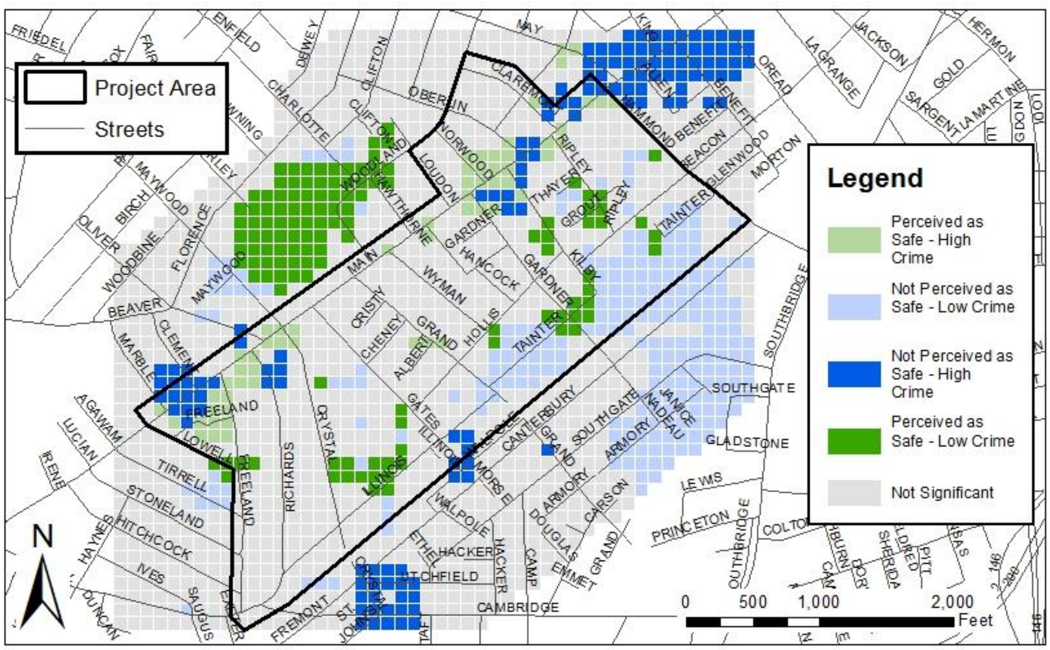


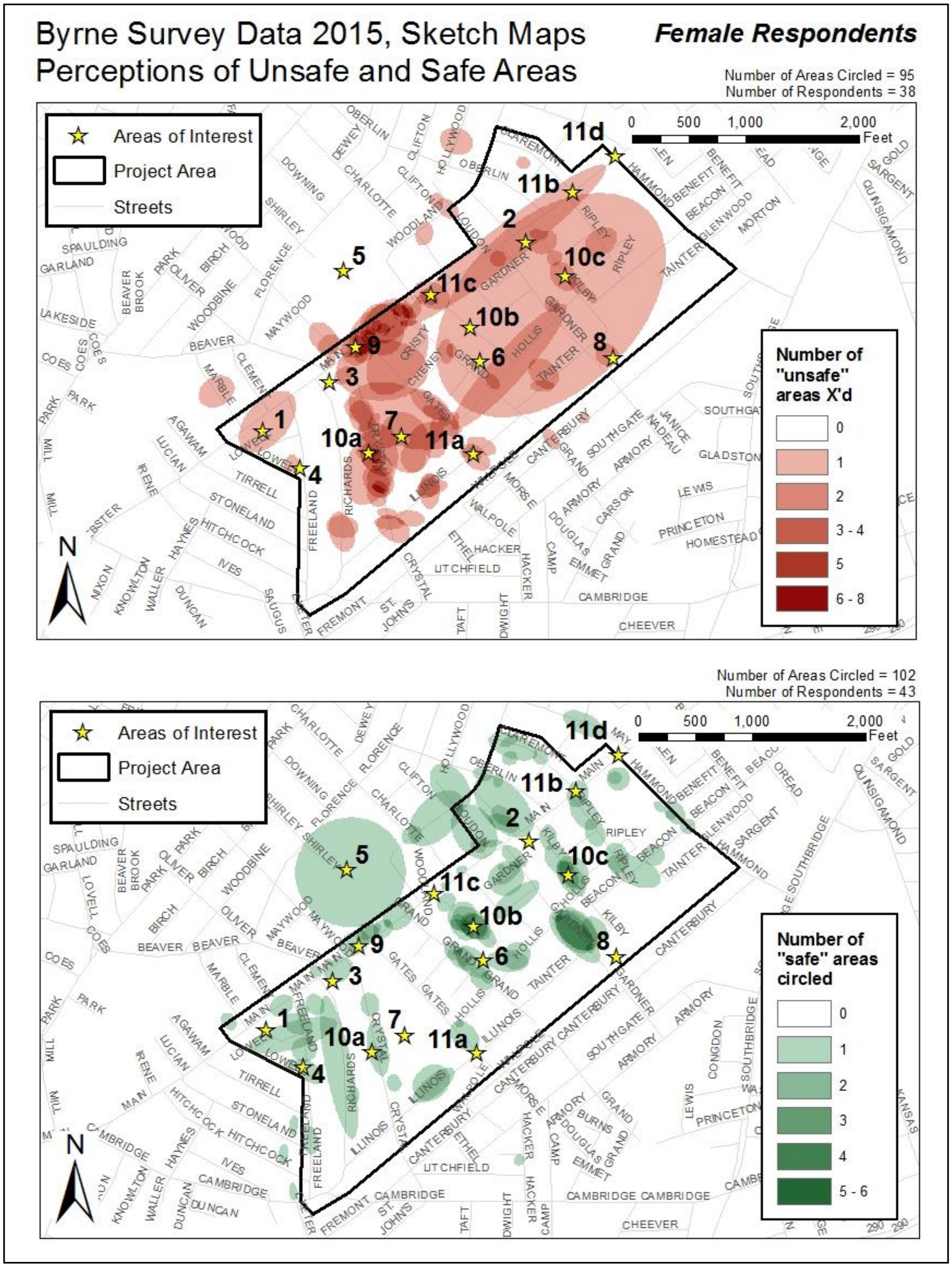
Author: Marina Khananayev February 2016
Sources: Worcester Police Department Crime Data from 2011-2014, MassGIS

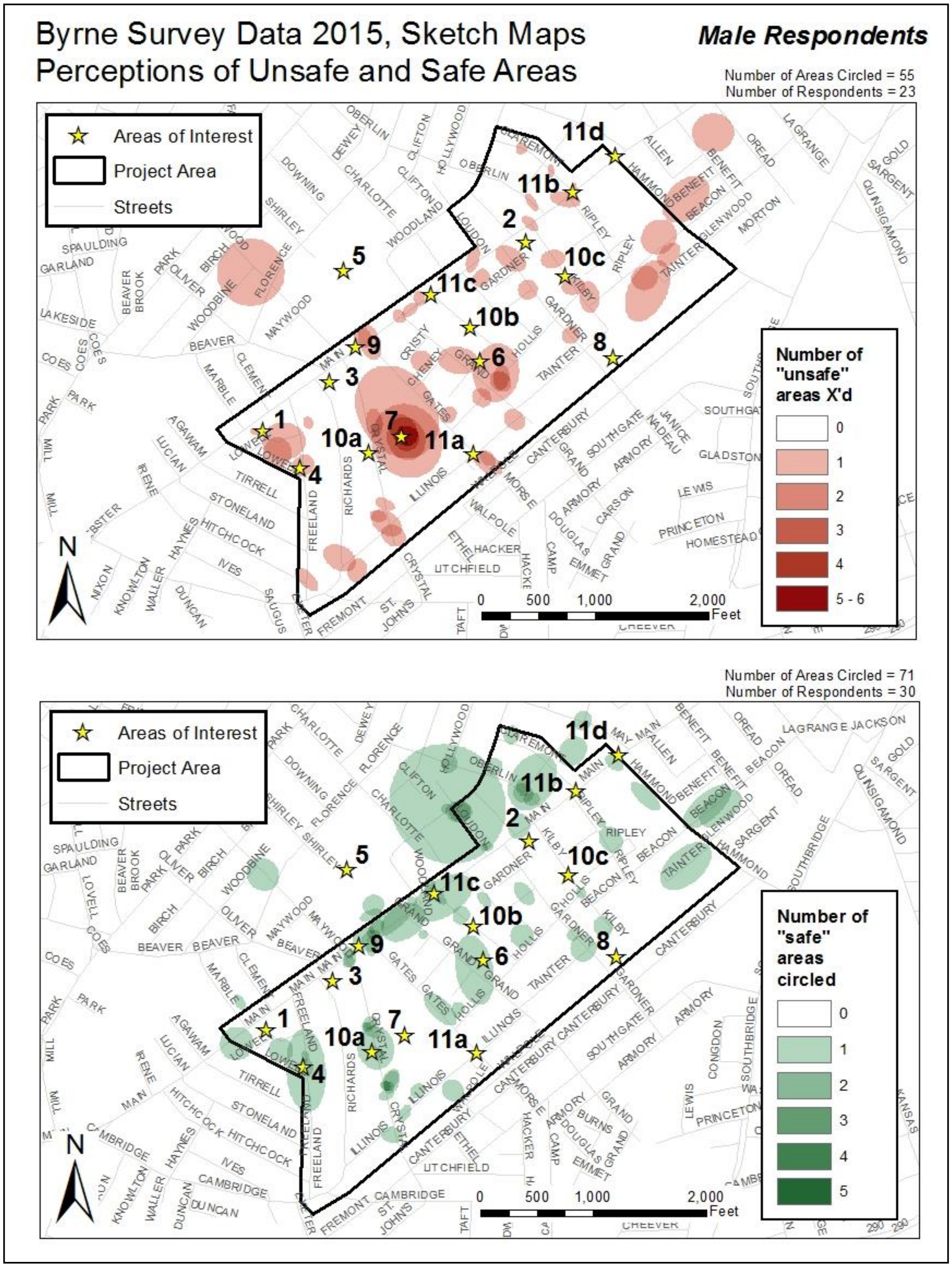
Perceptions of Unsafe and Safe Areas
Compared with Reported Crimes from 2011-2014
Bivariate LISA Cluster Analysis

All Respondents



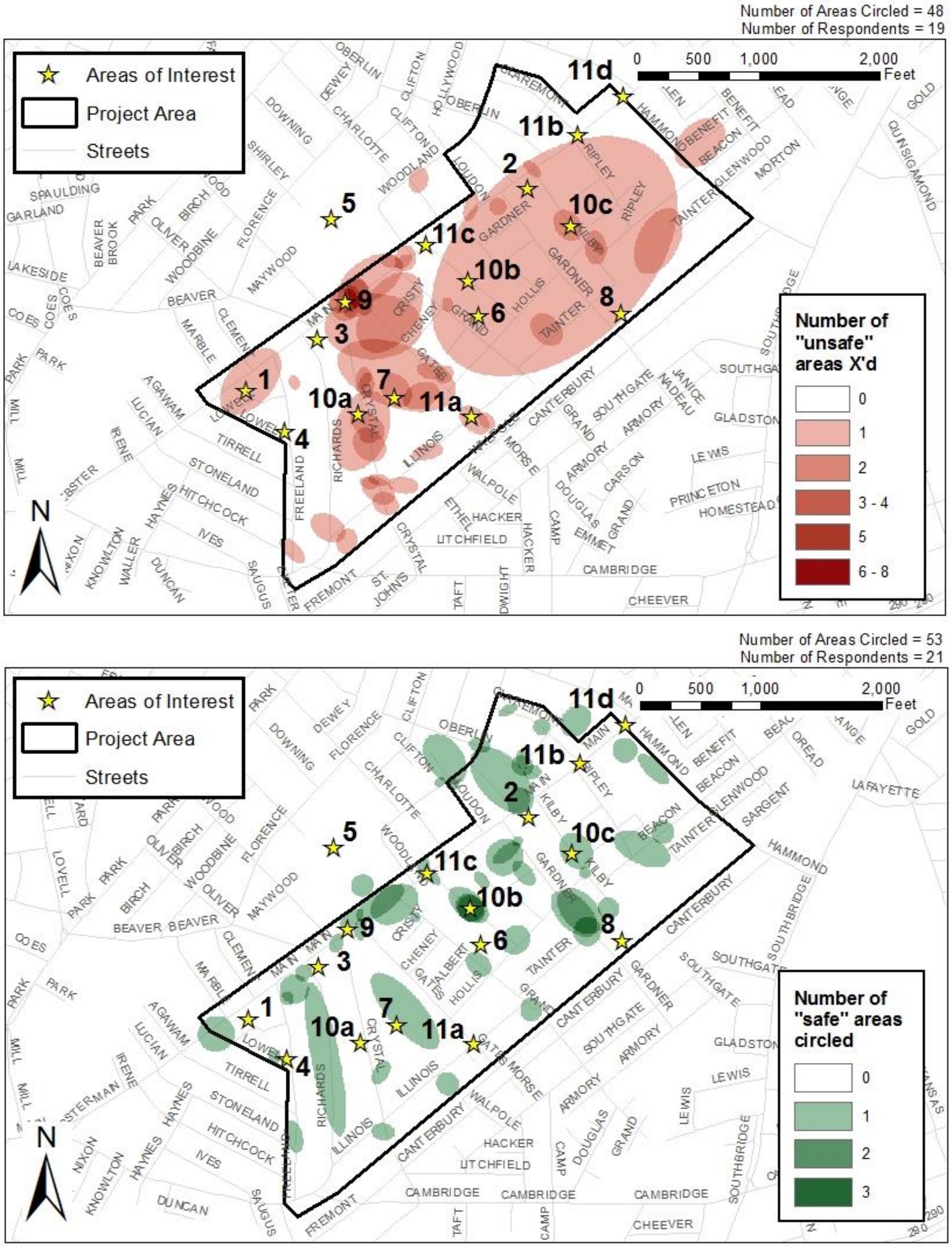


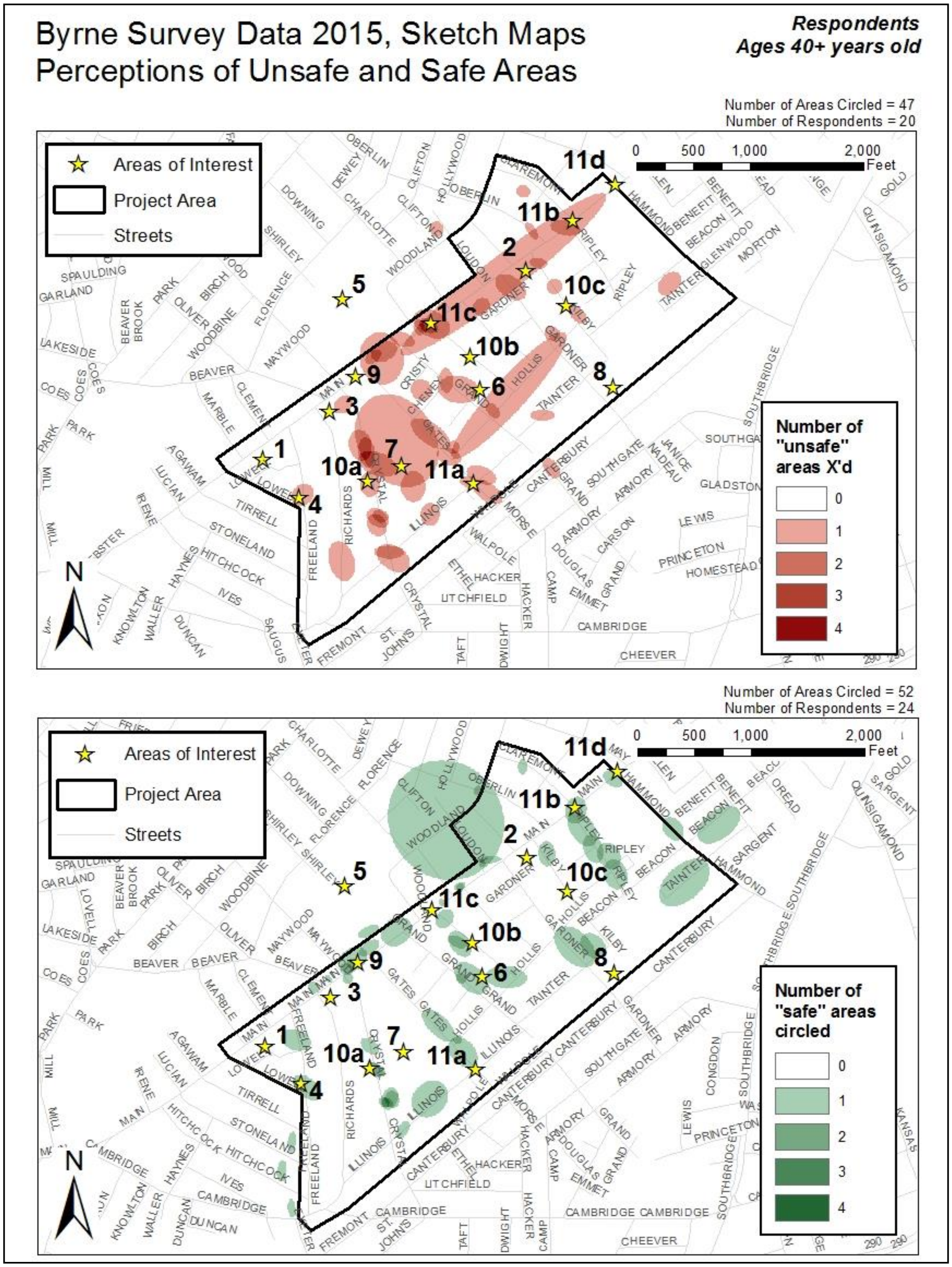

Byrne Survey Data 2015, Sketch Maps
Perceptions of Unsafe and Safe Areas
Female Respondents
Number of Areas Circled = 95
Number of Respondents = 38
Areas of Interest
Project Area
Streets
0 500 1,000 2,000 Feet
1
2
3
4
5
6
7
8
9
10a
10b
10c
11a
11b
11c
11d
N
Number of "unsafe" areas X'd
0
1
2
3 - 4
5
6 - 8
Number of Areas Circled = 102
Number of Respondents = 43
Areas of Interest
Project Area
Streets
0 500 1,000 2,000 Feet
1
2
3
4
5
6
7
8
9
10a
10b
10c
11a
11b
11c
11d
N
Number of "safe" areas circled
0
1
2
3
4
5 - 6

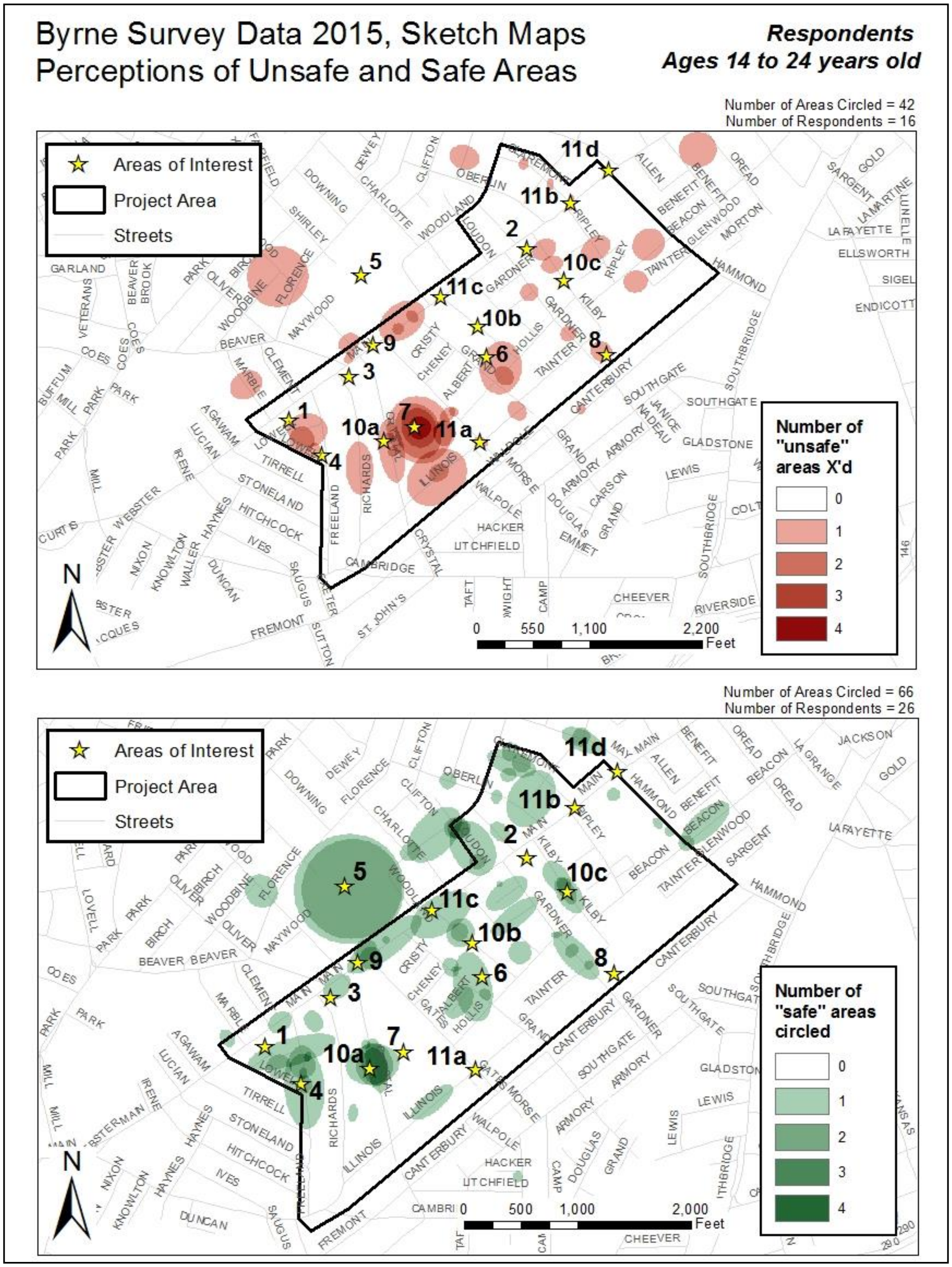

Byrne Survey Data 2015, Sketch Maps
Perceptions of Unsafe and Safe Areas
Male Respondents
Number of Areas Circled = 55
Number of Respondents = 23
Areas of Interest
Project Area
Streets
Number of "unsafe" areas X'd
0
1
2
3
4
5 - 6
0 500 1,000 2,000 Feet
Number of Areas Circled = 71
Number of Respondents = 30
Areas of Interest
Project Area
Streets
Number of "safe" areas circled
0
1
2
3
4
5
0 500 1,000 2,000 Feet

Byrne Survey Data 2015, Sketch Maps
Perceptions of Unsafe and Safe Areas

Respondents
Ages 25 to 40 years old



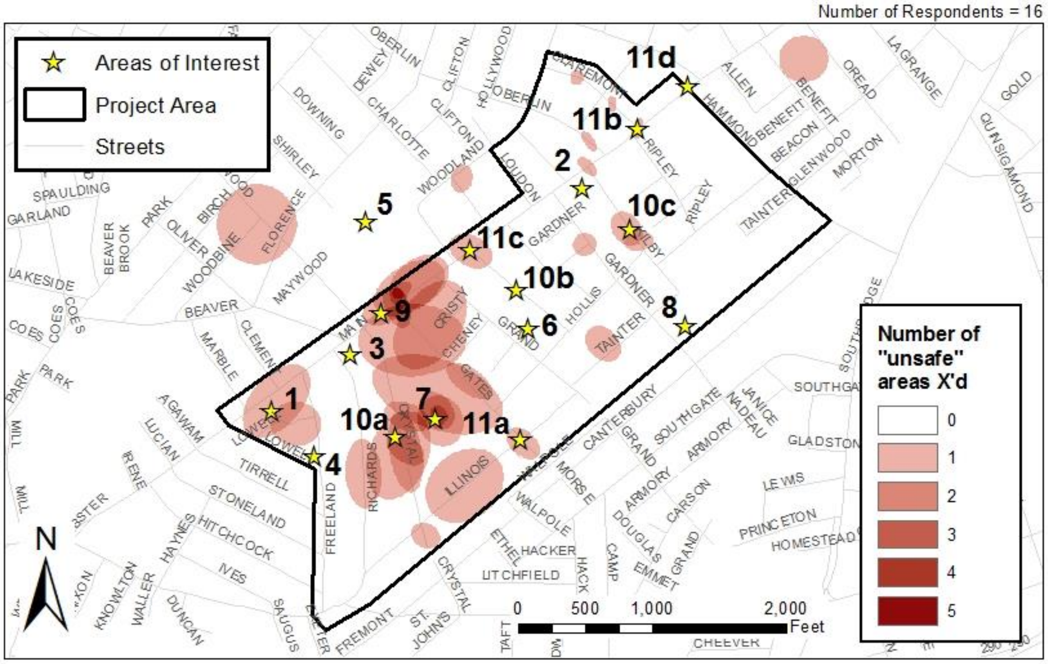

Byrne Survey Data 2015, Sketch Maps
Perceptions of Unsafe and Safe Areas
Respondents
Ages 40+ years old
Number of Areas Circled = 47
Number of Respondents = 20
Areas of Interest
Project Area
Streets
0 500 1,000 2,000 Feet
N
1
2
3
4
5
6
7
8
9
10a
10b
10c
11a
11b
11c
11d
Number of "unsafe" areas X'd
0
1
2
3
4
Number of Areas Circled = 52
Number of Respondents = 24
Areas of Interest
Project Area
Streets
0 500 1,000 2,000 Feet
N
Number of "safe" areas circled
0
1
2
3
4


Byrne Survey Data 2015, Sketch Maps
Perceptions of Unsafe and Safe Areas
Respondents
Ages 14 to 24 years old
Number of Areas Circled = 42
Number of Respondents = 16
Areas of Interest
Project Area
Streets
Number of "unsafe" areas X'd
0
1
2
3
4
0 550 1,100 2,200 Feet
N
Number of Areas Circled = 66
Number of Respondents = 26
Areas of Interest
Project Area
Streets
Number of "safe" areas circled
0
1
2
3
4
0 500 1,000 2,000 Feet
N

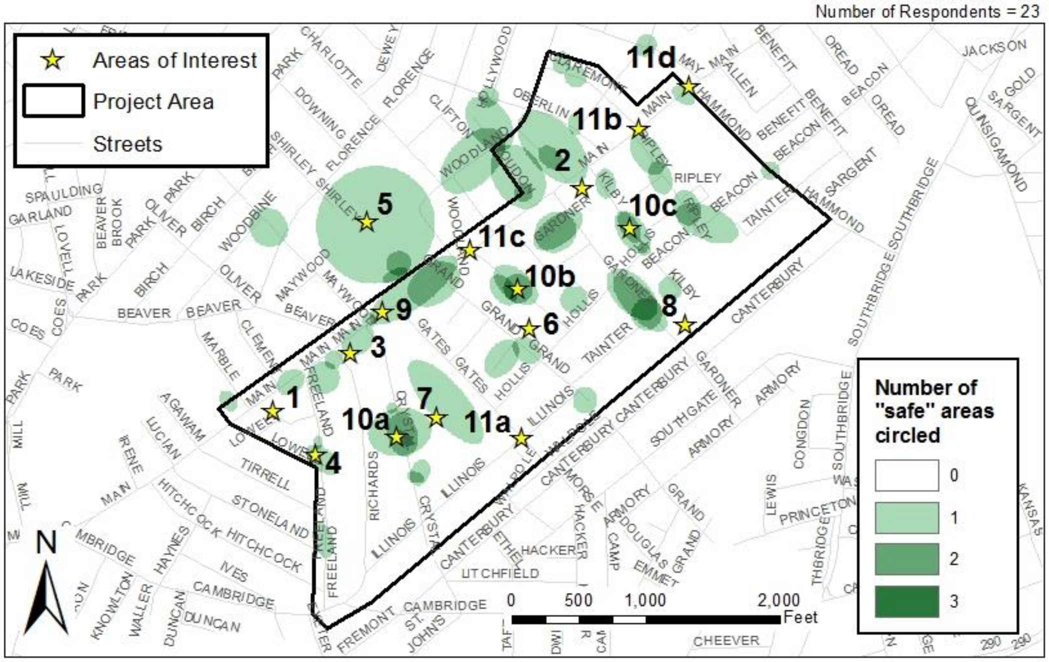
Byrne Survey Data 2015, Sketch Maps
Perceptions of Unsafe and Safe Areas

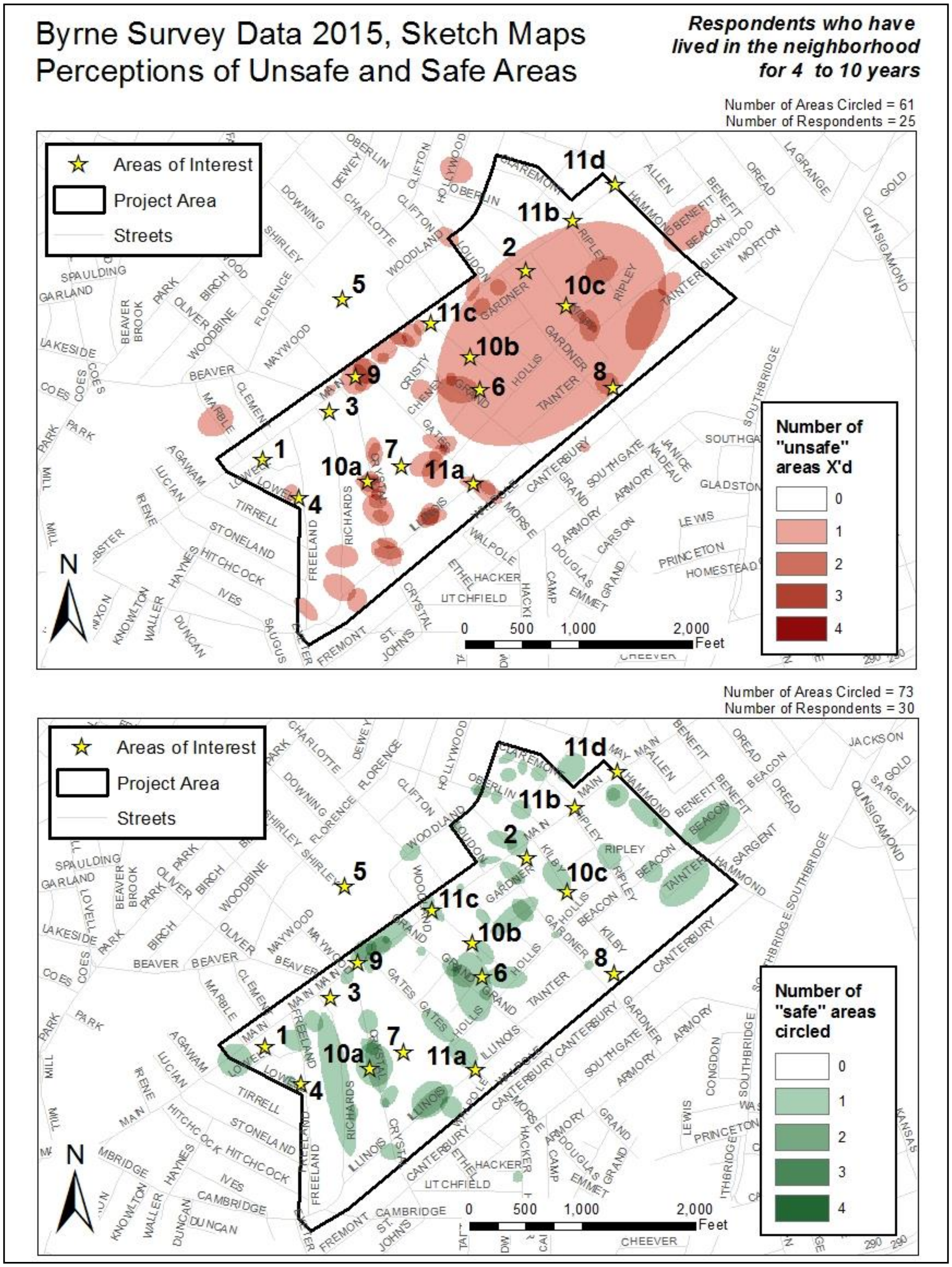
Respondents who have lived in the neighborhood for less than 3 years

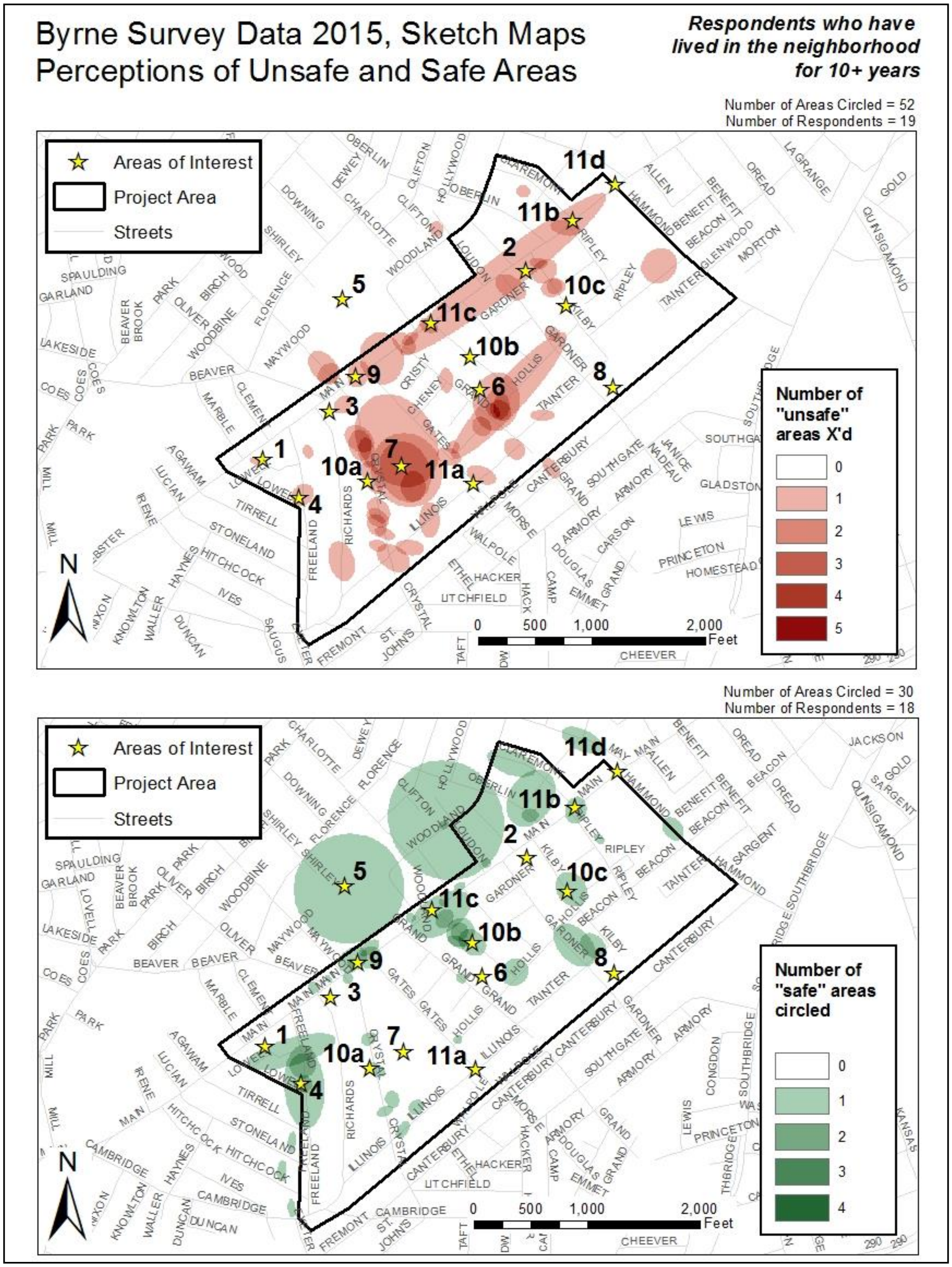
Number of Areas Circled = 35
Number of Respondents = 16

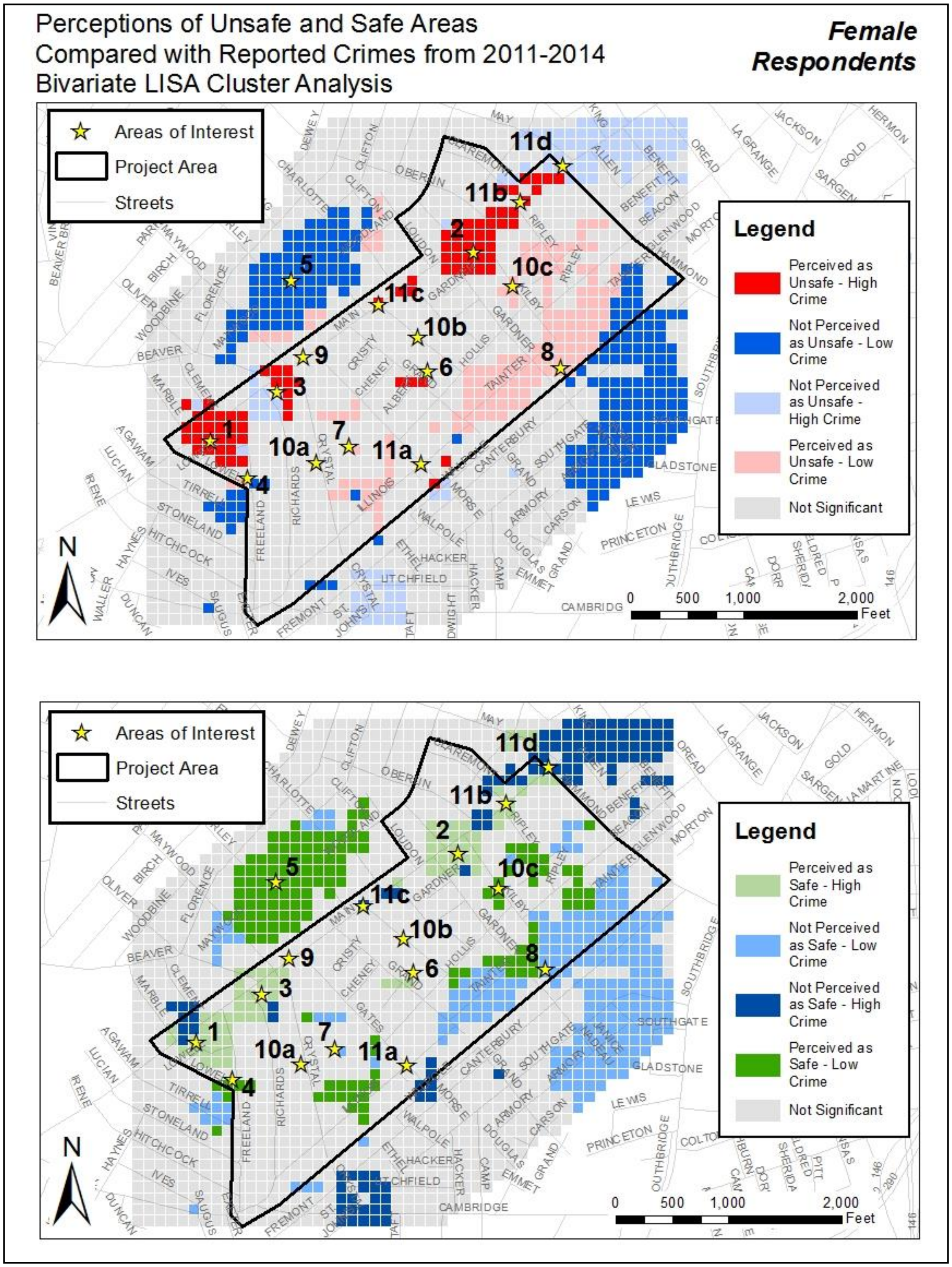


Number of Areas Circled = 56
Number of Respondents = 23



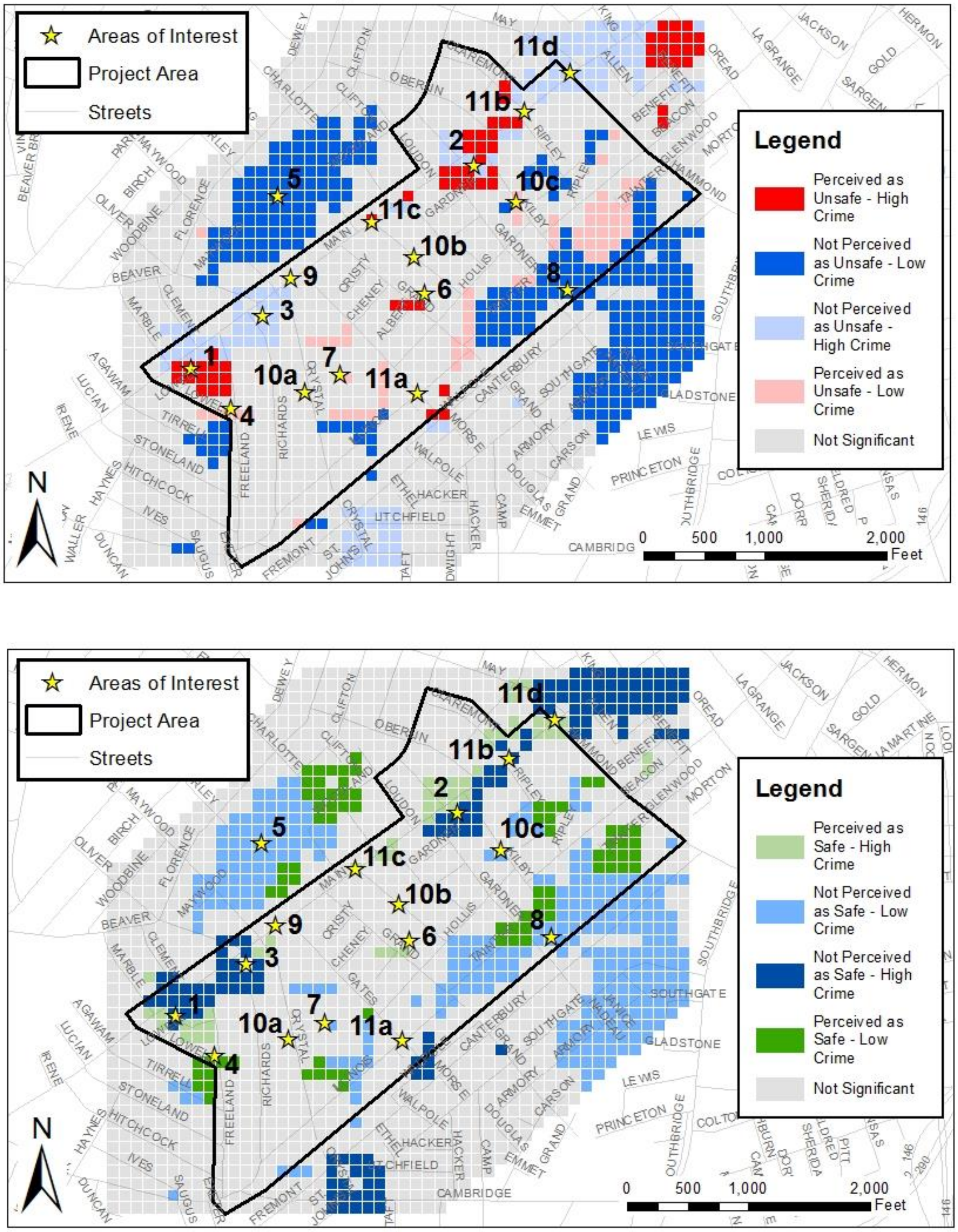

Byrne Survey Data 2015, Sketch Maps
Perceptions of Unsafe and Safe Areas
Respondents who have lived in the neighborhood for 4 to 10 years
Number of Areas Circled = 61
Number of Respondents = 25
Areas of Interest
Project Area
Streets
Number of "unsafe" areas X'd
0
1
2
3
4
N
0 500 1,000 2,000 Feet
1 2 3 4 5 6 7 8 9 10a 10b 10c 11a 11b 11c 11d
Number of Areas Circled = 73
Number of Respondents = 30
Areas of Interest
Project Area
Streets
Number of "safe" areas circled
0
1
2
3
4
N
0 500 1,000 2,000 Feet
1 2 3 4 5 6 7 8 9 10a 10b 10c 11a 11b 11c 11d

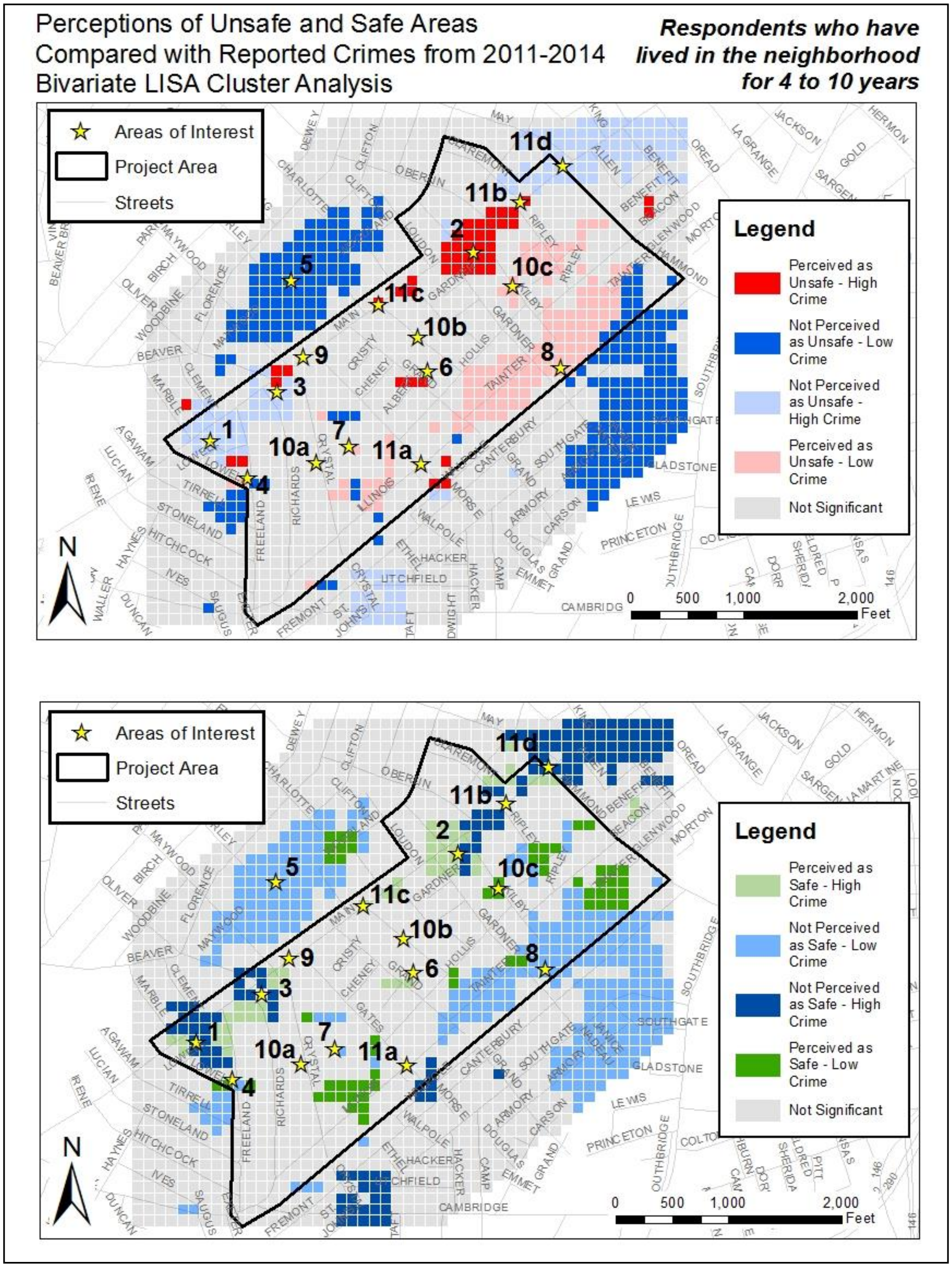

Byrne Survey Data 2015, Sketch Maps
Perceptions of Unsafe and Safe Areas
Respondents who have lived in the neighborhood for 10+ years
Number of Areas Circled = 52
Number of Respondents = 19
Areas of Interest
Project Area
Streets
Number of "unsafe" areas X'd
0
1
2
3
4
5
1
2
3
4
5
6
7
8
9
10a
10b
10c
11a
11b
11c
11d
N
0 500 1,000 2,000 Feet
Number of Areas Circled = 30
Number of Respondents = 18
Areas of Interest
Project Area
Streets
Number of "safe" areas circled
0
1
2
3
4
1
2
3
4
5
6
7
8
9
10a
10b
10c
11a
11b
11c
11d
N
0 500 1,000 2,000 Feet

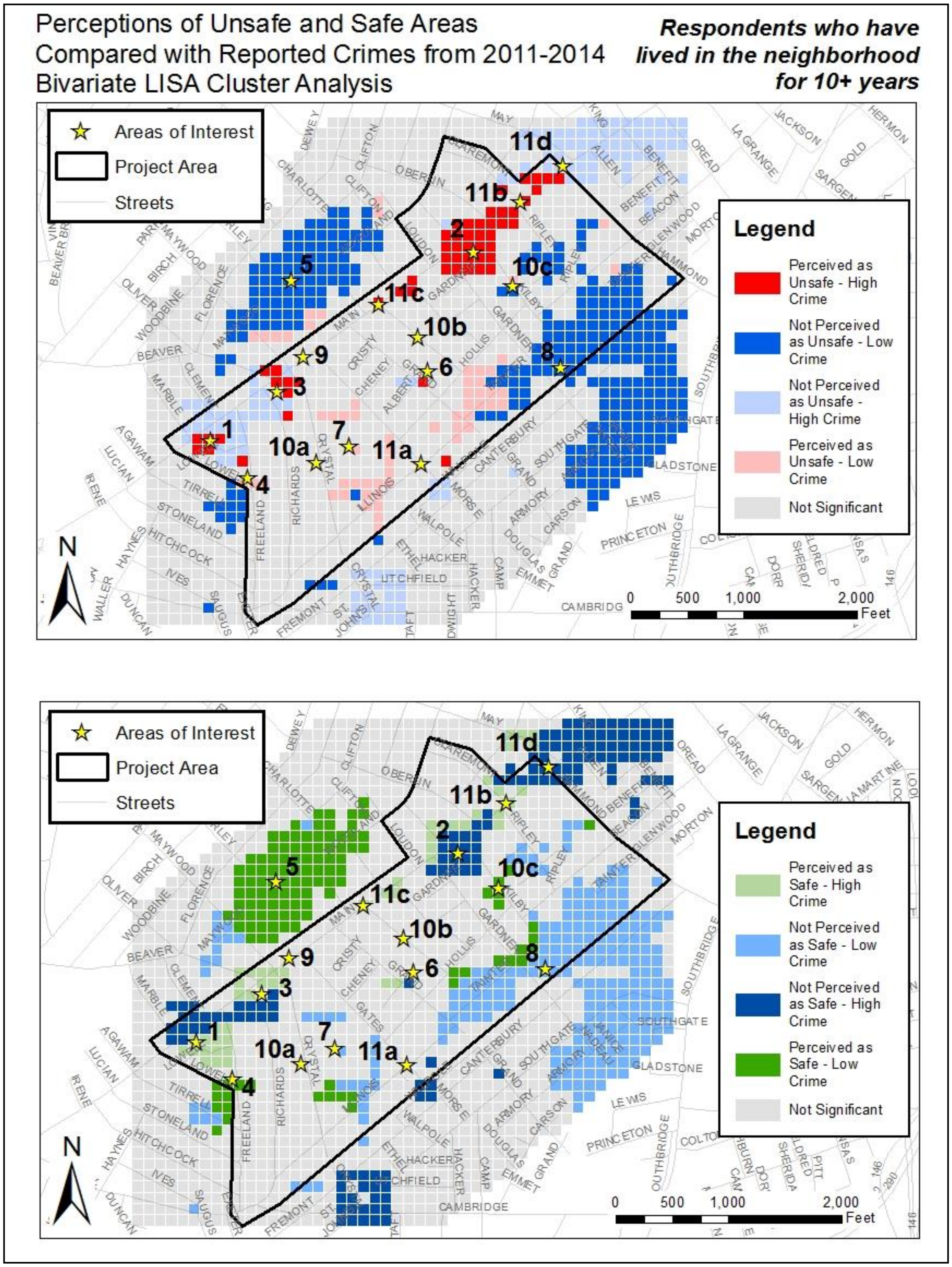

Perceptions of Unsafe and Safe Areas
Compared with Reported Crimes from 2011-2014
Bivariate LISA Cluster Analysis
Female Respondents
Areas of Interest
Project Area
Streets
Legend
Perceived as Unsafe - High Crime
Not Perceived as Unsafe - Low Crime
Not Perceived as Unsafe - High Crime
Perceived as Unsafe - Low Crime
Not Significant
0 500 1,000 2,000 Feet
N
Areas of Interest
Project Area
Streets
Legend
Perceived as Safe - High Crime
Not Perceived as Safe - Low Crime
Not Perceived as Safe - High Crime
Perceived as Safe - Low Crime
Not Significant
0 500 1,000 2,000 Feet
N

Perceptions of Unsafe and Safe Areas
Compared with Reported Crimes from 2011-2014
Bivariate LISA Cluster Analysis

Male Respondents



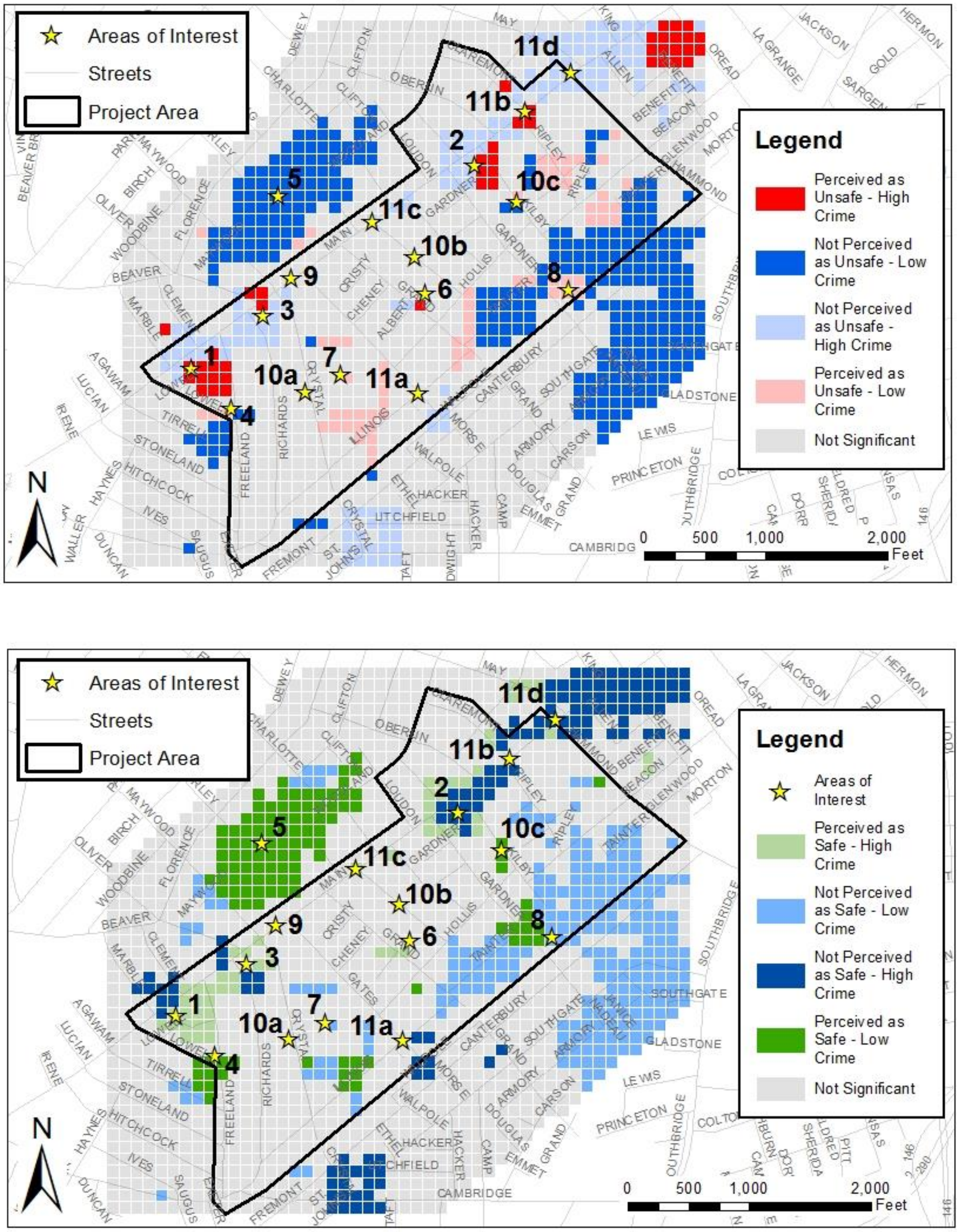

Perceptions of Unsafe and Safe Areas
Compared with Reported Crimes from 2011-2014
Bivariate LISA Cluster Analysis
Respondents who have lived in the neighborhood for 4 to 10 years
Areas of Interest
Project Area
Streets
Legend
Perceived as Unsafe - High Crime
Not Perceived as Unsafe - Low Crime
Not Perceived as Unsafe - High Crime
Perceived as Unsafe - Low Crime
Not Significant
0 500 1,000 2,000 Feet
N
Areas of Interest
Project Area
Streets
Legend
Perceived as Safe - High Crime
Not Perceived as Safe - Low Crime
Not Perceived as Safe - High Crime
Perceived as Safe - Low Crime
Not Significant
0 500 1,000 2,000 Feet
N

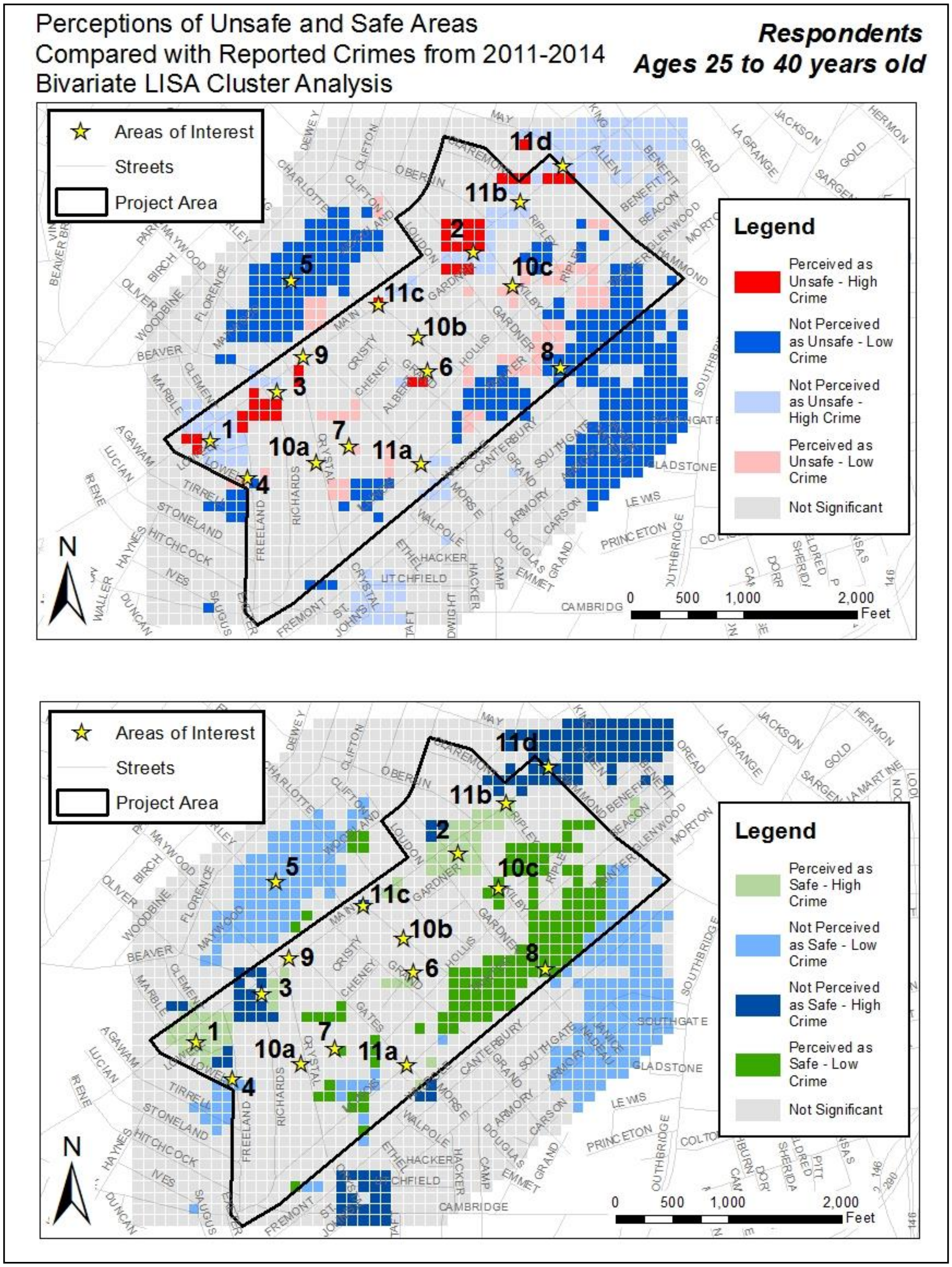


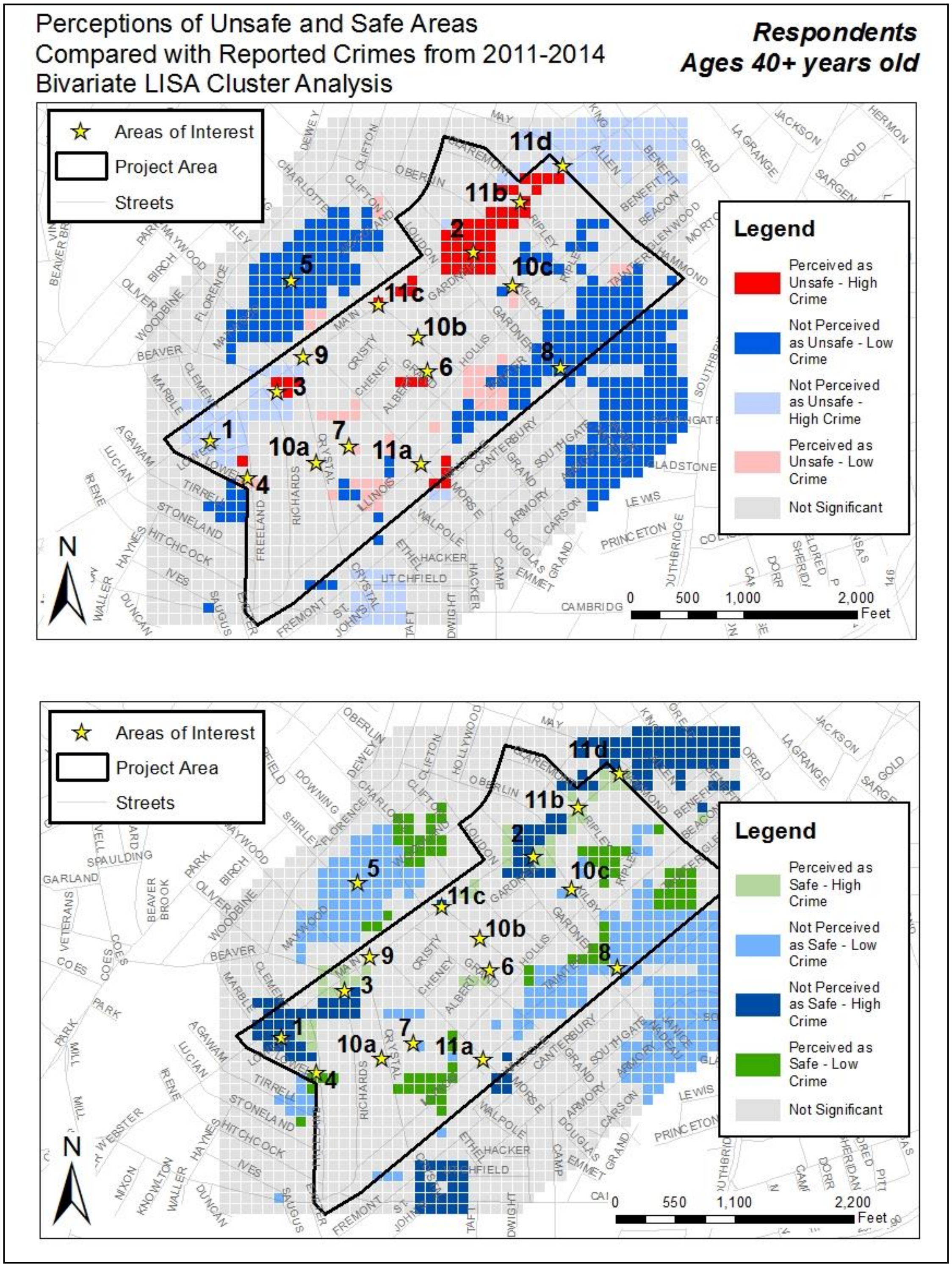
Perceptions of Unsafe and Safe Areas
Compared with Reported Crimes from 2011-2014
Bivariate LISA Cluster Analysis
Respondents who have lived in the neighborhood for 10+ years
Areas of Interest
Project Area
Streets
Legend
Perceived as Unsafe - High Crime
Not Perceived as Unsafe - Low Crime
Not Perceived as Unsafe - High Crime
Perceived as Unsafe - Low Crime
Not Significant
0 500 1,000 2,000 Feet
N
Areas of Interest
Project Area
Streets
Legend
Perceived as Safe - High Crime
Not Perceived as Safe - Low Crime
Not Perceived as Safe - High Crime
Perceived as Safe - Low Crime
Not Significant
0 500 1,000 2,000 Feet
N

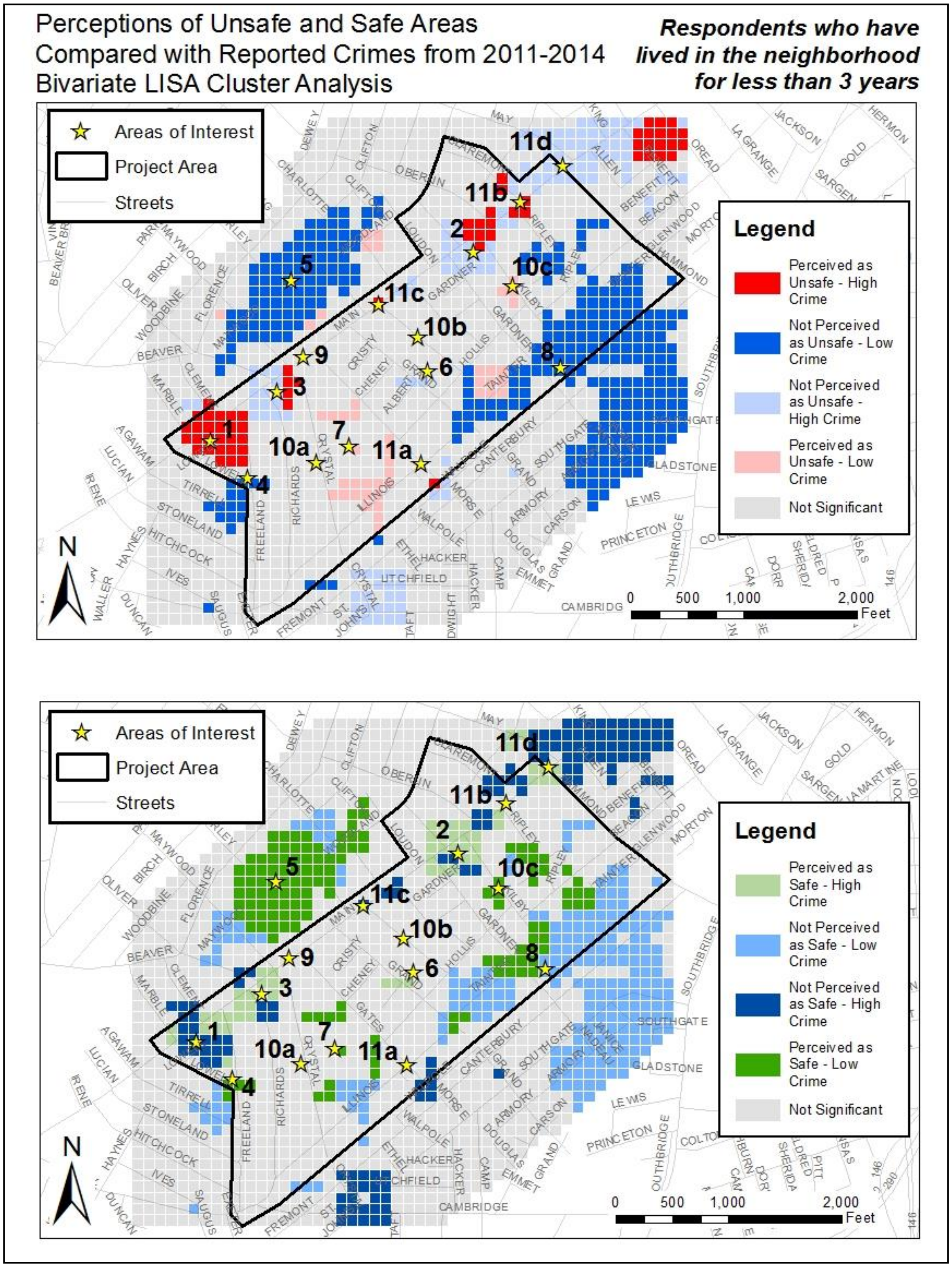
Perceptions of Unsafe and Safe Areas
Compared with Reported Crimes from 2011-2014
Bivariate LISA Cluster Analysis

Respondents
Ages 14 to 24 years old




Perceptions of Unsafe and Safe Areas
Compared with Reported Crimes from 2011-2014
Bivariate LISA Cluster Analysis
Respondents
Ages 25 to 40 years old
Areas of Interest
Streets
Project Area
Legend
Perceived as Unsafe - High Crime
Not Perceived as Unsafe - Low Crime
Not Perceived as Unsafe - High Crime
Perceived as Unsafe - Low Crime
Not Significant
0 500 1,000 2,000 Feet
N
Areas of Interest
Streets
Project Area
Legend
Perceived as Safe - High Crime
Not Perceived as Safe - Low Crime
Not Perceived as Safe - High Crime
Perceived as Safe - Low Crime
Not Significant
0 500 1,000 2,000 Feet
N


Perceptions of Unsafe and Safe Areas
Compared with Reported Crimes from 2011-2014
Bivariate LISA Cluster Analysis
Respondents
Ages 40+ years old
Areas of Interest
Project Area
Streets
Legend
Perceived as Unsafe - High Crime
Not Perceived as Unsafe - Low Crime
Not Perceived as Unsafe - High Crime
Perceived as Unsafe - Low Crime
Not Significant
0 500 1,000 2,000 Feet
Areas of Interest
Project Area
Streets
Legend
Perceived as Safe - High Crime
Not Perceived as Safe - Low Crime
Not Perceived as Safe - High Crime
Perceived as Safe - Low Crime
Not Significant
0 550 1,100 2,200 Feet


Perceptions of Unsafe and Safe Areas
Compared with Reported Crimes from 2011-2014
Bivariate LISA Cluster Analysis
Respondents who have lived in the neighborhood for less than 3 years
Areas of Interest
Project Area
Streets
Legend
Perceived as Unsafe - High Crime
Not Perceived as Unsafe - Low Crime
Not Perceived as Unsafe - High Crime
Perceived as Unsafe - Low Crime
Not Significant
0 500 1,000 2,000 Feet
Areas of Interest
Project Area
Streets
Legend
Perceived as Safe - High Crime
Not Perceived as Safe - Low Crime
Not Perceived as Safe - High Crime
Perceived as Safe - Low Crime
Not Significant
0 500 1,000 2,000 Feet