TESTING A GEOSPATIAL PREDICTIVE POLICING STRATEGY:

APPLICATION OF ARCGIS 3D ANALYST TOOLS

FOR FORECASTING COMMISSION OF

RESIDENTIAL BURGLARIES

By

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…

I believe spatial design and configurations influence health and safety. Thus, I would like to thank "institutions, agencies and organizations that initiate, support and value design research programs."

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ABSTRACT

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Classical placed-based crime prevention theories suggest existence of a relationship between certain characteristics of spatial design and configuration and crime occurrence. This study explored the relationship between natural surveillance – one of the least studied and understood principles of crime prevention through environmental design (CPTED) – and burglary commissions in three-dimensions.

Natural surveillance has been claimed to differ when seen by neighbors, pedestrian passersby or individuals in vehicles, and to be influenced by viewing distance. Thus, the notion of natural surveillance was quantified to three categories of occupant, road and pedestrian surveillability. In addition, length of sightlines were restricted by the distance at which human eye is considered effective to eyewitness and interpret events.

Employing a mixed methods research design, qualitative data (sketches made from oblique aerial imagery, field observations of architectural and landscape features, burglary crime reports and field observations of crime sites) were embedded and provided a supportive role for the quantitative data (georeferenced spatial and crime data) and quantitative analysis (univariate and multivariate statistical analysis). Firstly, ArcGIS geospatial tools were utilized for processing spatial and crime data in three-dimensions. Then, ESRI ModelBuilder was employed for automating the procedure of enumerating natural surveillance intensity.

Spearman's rank correlation, Mann-Whitney U and binary logistic regression were employed to investigate the univariate and multivariate association between natural surveillance and burglary commissions or burglary occurrence. The results at the building opening level revealed that the log of the odds of burglary commission was negatively related to occupant surveillability and positively related to road surveillability. Findings at the building level showed that the log of the odds of residential burglary occurrence was positively related to road surveillability.

This research shed light on the importance of the notion of "eyes upon the street" (Jacobs, 1961) even in a low socioeconomic-high criminogenic area. It has implications for developing proactive design and planning policies to help design crime out at the early stages of planning and development. It also demonstrates how law enforcement can further leverage societal investments in geospatial data to benefit public safety more effectively.

KEYWORDS: Eyes upon the Street, Geographic Information Systems (GIS), Natural Surveillance, Residential Burglary, 3D, Line-of-sight.

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Dedication

This dissertation is dedicated to

My mother and father
(Zari and Manouchehr)

&

My brothers
(Ali and Omid)

1 INTRODUCTION

1.1 Introduction

Living in crime-free environments is one of the main desires of human beings. However, crime and fear of crime are pervasive and experienced in routine everyday life. One pervasive crime, burglary is the focus of this dissertation. Approximately every 14 seconds a burglary is committed in the United States (FBI, 2010b). In the year 2010, burglary constituted 23.8 percent of property crimes, of which 73.9 percent were residential burglaries (FBI, 2010b). In that same year, the burglary crime rate was 699.6 per 100,000 inhabitants. This rate in cities outside metropolitan areas far exceeded that in metropolitan statistical areas and nonmetropolitan counties. The burglary crime rate was 819.9 per 100,000 inhabitants in cities outside metropolitan areas and 706.5 and 559.7 per 100,000 inhabitants in metropolitan statistical areas and nonmetropolitan counties respectively (FBI, 2010b).

Even though the burglary rate has decreased over the last 20 years, the number of burglaries between 2006-2010 has increased when compared with the 2001-2005 estimates (FBI, 2010a). In addition, the tangible costs of burglaries remain high and have been rising - while in 2006 approximately $4.0 billion was stolen from burglarized victims, that number increased to $4.6 billion in 2010 (FBI, 2010a). Those figures constituted approximately 2.8 and 3.1 percent of the United States GDP in years 2006 and 2010 respectively (CIA, 2012).

Furthermore, while the average dollar loss per residential burglary offense was $1,823 in year 2006, that number increased to $2,137 in year 2010 (FBI, 2010b). Lastly, even though placing monetary units on tangible costs of burglaries is rather feasible, assigning monetary units on intangible costs of crimes is still in debate (M. A. Cohen, 2001). Crime victims suffer from pain, grief and suffering among other psychological distress of crimes (Dolan, Loomes, Peasgood, & Tsuchiya, 2005; Dolan & Peasgood, 2007). Hence, identifying factors that can reduce residential burglaries helps diminish not only the tangible costs of residential burglaries but also lessens the intangible costs that burglary imposes on communities as a whole.

Freedom from crime and fear of crime can be influenced by and related to certain characteristics of spatial design and configuration (P. J. Brantingham & P. L. Brantingham, 1981a, 1993; Cozens, Saville, & Hillier, 2005; Eck, 2002; Hillier, 2007; Jacobs, 1961; Jeffery, 1977; Newman, 1973; Reynald, 2011a, 2011b; Weisburd, Groff, & Yang, 2012). One of the main qualities of spatial design postulated to promote freedom from criminal activities is natural surveillance. The concept of natural surveillance was first discussed by Jane Jacobs (1961). In coining the term "eyes upon the street," Jacobs postulated natural surveillance can be facilitated by spatial configurations that offer residents and guardians opportunities to survey non-private spaces of residential settings (Jacobs, 1961; Newman, 1973, 1996). For that reason, architecture (building design, urban design and planning) ought to "… create spaces that are easily viewed by residents, neighbors and bystanders" (Katyal, 2002, p. 1050).

Natural surveillance has been claimed to differ when seen by neighbors, pedestrian passersby or individuals in vehicles. Therefore, the notion of natural surveillance has been categorized into occupant and road/pedestrian surveillability (Brown & Altman, 1981;

Macdonald & Gifford, 1989; Van Nes & López, 2010). Occupant surveillability measures visibility of building openings as seen by neighboring building openings. The road and pedestrian surveillability show visibility of building openings as seen from roads or sidewalks respectively.

1.2 Statement of the Problem

Outdated or untested measures in crime analysis and prevention make it difficult to accurately and objectively assess; (1) what crime prevention policies and practices are most appropriate for neighborhoods with different socio-economic characteristics; (2) how neighborhood residents might effectively deter crime in their neighborhoods, and (3) how law enforcement officers and agencies can help deter crime in neighborhoods. This study was designed to help shed light on these important considerations in crime analysis and prevention strategies.

For instance, computer comparison statistics (CompStat) is a management model devised by William Bratton, commissioner of police in New York City. Through mapping crime, identifying crime hotspots and managing law enforcement personnel and resources accordingly, CompStat seeks to reduce crime and improve quality of life (Bratton, 1998; Kelling & Bratton, 1998). Even though the number of law enforcement agencies using CompStat or CompStat-like programs has increased in recent years (Weisburd, Mastrofski, McNally, Greenspan, & Willis, 2003), it is not possible to effectively analyze crime without valid and sufficiently accurate measures of the physical environment's configuration and its association with crime occurrence.

Our ability to measure and quantify spatial design and configurations in general and natural surveillance in particular has changed drastically in the era of the digital spatial information revolution (LeGates, Tate, & Kingston, 2009), yet we still have not fully utilized emerging technologies to quantify natural surveillance in three dimensions. Nor have we scientifically tested whether emerging technologies can help us better comprehend the existence of a relationship between natural surveillance and commission of crimes. Not taking advantage of emerging techniques, continuing to analyze crime through aggregating or counting the number of incidents by using CompStat or CompStat-like tools and excluding spatial characteristics of crime sites in crime analysis cannot help us objectively detect at finer scales the existence and the extent of a relationship between the configuration of the physical environment and commission of crimes.

I quantified and included spatial characteristics of crime sites in crime analysis. My study tested the extent to which georeferenced data and geospatial technologies can help us objectively quantify the notion of "eyes upon the street" (Jacobs, 1961) in three dimensions and to then compared burglary commissions with the degree or intensity of natural surveillance. The current study is, to my knowledge, the only study extant that seeks to objectively quantify and understand the effectiveness of the notion of "eyes upon the street" in three dimensions in deterring residential burglary commissions.

1.3 Statement of Purpose

The purpose of this study was to quantify and clarify the extent of natural surveillance necessary to discourage residential burglaries. Additionally, this study sought to create an enhanced model and methodology for studying other crimes with a natural surveillance component (i.e. graffiti, car theft, etc.). Even though previous research supports existence of an inverse relationship between natural surveillance and occurrence of crimes (Bellair, 2000; Coupe & Blake, 2006; Van Nes & López, 2010), researchers' ability to quantify the extent of natural surveillance necessary to deter crime is limited. Thus, through utilization of geo-referenced data, geospatial technologies and multi-level analysis, the model developed in this dissertation delineated which building openings (i.e. doors, windows, etc.) and buildings might have a higher probability of burglary occurrence. This study purpose included the following objectives:

- Identify architectural and landscape features that directly influence variations in intensity of natural surveillance.
- Identify model covariates that influence variations in crime.
- Develop a method for quantifying architectural and landscape features.
- Develop a method for quantifying natural surveillance in three dimensions.
- Document whether or not natural surveillance has a significant effect on commission and deterrence of residential burglaries.

A review of literature helped with identification of architectural and landscape features and model covariates that influence intensity of natural surveillance and variations in crime. Next, geospatial data and technologies were utilized to create two dimensional and three dimensional georeferenced datasets quantifying architectural and landscape features and model covariates. Natural surveillance, categorized into three categories of occupant, road and pedestrian surveillability, was then enumerated and quantified through utilization of visual programming geospatial tools. Based on analysis of police crime reports, the actual burglary entry points were then compared to the measured intensity of natural surveillance. This method facilitated detailed analysis of surveillance characteristics of building openings and buildings, leading in turn to achieving the goal of objectively understanding the effects of "eyes upon the street" (Jacobs, 1961) in deterring residential burglaries.

1.4 Research Questions

1. What is the relationship between the degree of occupant, road and pedestrian surveillability and commission of residential burglaries?
2. Does the degree of occupant, road and pedestrian surveillability differ between burglarized and non-burglarized building openings and buildings?
3. Can a burglar's point of entry be reliably predicted from the knowledge of occupant, road and pedestrian surveillability?
4. Can a residential burglary be reliably predicted from the knowledge of occupant, road and pedestrian surveillability?

1.5 Hypotheses

1. For building openings. There is a statistically significant inverse relationship between the degree of occupant, road and pedestrian surveillability and commission of residential burglaries.
2. For building openings. Burglarized building openings have statistically significant lower mean of occupant, road and pedestrian surveillability compared to non-burglarized building openings.

3. For building openings. A burglar’s point of entry can be reliably predicted from the knowledge of occupant, road and pedestrian surveillability.
4. For buildings. There is a statistically significant inverse relationship between the degree of occupant, road and pedestrian surveillability and residential burglary victimization.
5. For buildings. Burglarized buildings have statistically significant lower mean of occupant, road and pedestrian surveillability compared to non-burglarized buildings.
6. For buildings. A residential burglary can be reliably predicted from the knowledge of occupant, road and pedestrian surveillability.

1.6 Expected Outcomes

This study employed rigorous research design to develop and test a methodology for measuring the intensity of visual surveillance and to create and confine expectations regarding the most likely burglars’ entry points or burglary occurrence. In turn, such a capability will enable policymakers, researchers and law enforcement agencies to better comprehend and assess how crimes with a natural surveillance component can be addressed and deterred. The potential outcomes of this study include:

- Demonstrate how law enforcement can further leverage investment in geospatial data in most communities to benefit public safety more effectively.
- Show how law enforcement agencies can take advantage of research conducted in the field of design and planning in order to allocate their scarce resources to predictable crime hotspots.

- Develop a methodology for better comprehension and analysis of crimes with a natural surveillance component.
- Test whether or not CPTED principles are applicable in low socio-economic neighborhoods.
- Understand and compare crime occurrence at different scales of building opening, building and street segment.
- Compare the intensity of natural surveillance in different neighborhoods.
- Develop guidelines regarding strategic placement of architectural and landscape features.
- Develop appropriate planning and design policies to help prevent crime.

1.7 Summary of Chapters

Chapter 2 reviews classical place-based crime prevention theories, with an eye towards how natural surveillance has been measured and how its relationship to residential burglaries has been studied. Contemporary techniques facilitating studies of crimes with a natural surveillance component are also discussed.

Chapter 3 presents the research methodology. It describes techniques utilized for geocoding architectural and landscape features and the locations of burglaries. This chapter also describes the sources of spatial and crime data used for this study and reviews their applications, limitations and shortcomings. Georeferenced databases and variables developed for this study are discussed.

Chapter 4 focuses on the procedures developed to quantify and enumerate natural surveillance intensity. ESRI ModelBuilder, a visual programming tool for creating workflows is used for this purpose. Descriptions of input and output features or tables are presented.

Chapter 5 presents the results of descriptive and inferential statistics for exploring the relationship between natural surveillance and burglary commissions at two levels of building openings and buildings.

Chapter 6 discusses and draws conclusions based on the findings presented in analytical chapter in the light of questions and hypotheses specified in our introductory chapter. Limitations and implications of this research are also highlighted.

Appendix A provides a detailed description of procedures employed for site selection.

Appendix B shows examples of sketch maps drawn from oblique aerial imagery and maps produced for field observations.

Appendix C contains information on variations of natural surveillance intensity affected by each individual or combinations of architectural and landscape features.

Appendix D contains descriptive statistics on burglary commissions and residential burglaries. In addition, results of selected chi-square statistics on the relationship between burglary commissions and residential burglaries and model covariates are presented.

2 LITERATURE REVIEW

2.1 Introduction

This chapter discusses classical theories of place-based crime prevention, concentrating on the notion of natural surveillance as one of the least understood and studied principle of crime prevention through environmental design (CPTED). I then reviewed the status of current literature on the relationship between natural surveillance and residential burglaries, presenting how natural surveillance has been objectively or subjectively measured in previous studies. I last assessed how natural surveillance in the era of digital spatial information revolution can be objectively studies, mapped and quantified. I conclude this chapter by developing a conceptual framework for studying the relationship between natural surveillance and commission of residential burglaries.

2.2 Crime

Crime is an intricate interaction of several variables and processes from the time individuals decide to become criminals to occasions when they make decisions to commit criminal activities. In addition, there are formal and informal reactions to criminal activities; formal reactions are responses of law enforcement personnel to crime. Informal reactions are responses of communities and/or victims to being victimized. Lastly, crime occurs against a backcloth of the world culture of the time. Thus, social constructions, religious doctrines, social and political powers and international-national-state-local laws can sway the definition and classifications of crimes (Morrison, 2009). Morrison elaborated on some definitions for crime. Here, I present the definition which is most relevant for my research.

> Crime is an act or omission that is defined by the validly passed laws of the nation state in which it occurred so that punishment should follow from the behaviour. Only such acts or omissions are crimes. (Morrison, 2009, p. 12)

In the United States, criminal law and prosecution take place at the federal, states and local level. The Federal Bureau of Investigation (FBI, 2010a) collects and archives data on crime. The FBI reports crime under two broad categories: "violent crime" and "property crime."[1] Violent crimes, involving force or force threat, are comprised of four offenses; (a) murder and non-negligent manslaughter, (b) forcible rape, (c) robbery and (d) aggravated assault. Property crimes, not involving force or force peril, encompass; (a) burglary, (b) larceny theft, (c) motor vehicle theft and (d) arson.

The Uniform Crime Report (UCR) outlines burglary as "the unlawful entry of a structure to commit a felony or theft" (FBI, 2010b). Property crimes encompass a stronger spatial visibility component compared to violent crimes meaning that potential criminals take into account whether they may be seen, reported to and arrested by the police while committing crimes. I have selected to study residential burglaries because residential burglaries constitute a large percentage of burglaries and information on exact locations of residential burglaries is transcribed in crime reports.

[1] Some other categorizations for crime exist. For instance, Boba (2009) categorized crime into person crime and property crime. Person crime includes robbery, stranger sexual assault, indecent exposure and public sexual indecency. Property crime encompasses theft from vehicle, auto theft, residential burglary and commercial burglary.

2.3 Classical Theories of Place-Based Crime Prevention

Schneider and Kitchen (2007) discussed the seminal literature on crime prevention under the term of "classical theories of place-based crime prevention" (p. 15). I selected Schneider & Kitchen's term to discuss environmental criminology, crime prevention through environmental design (CPTED) and situational crime prevention as the primary concepts of classical placed-based crime prevention theories. Placing emphasis on spatiotemporal aspects of crime occurrence, classical place-based crime prevention theories have roots in the fields of criminology, geography, planning, psychology and sociology among others.

2.3.1 Environmental criminology

Environmental criminology diverges from other traditional criminology theories in that instead of deliberating on the root causes of crime and reasons for becoming criminals, emphasis is placed on spatial and temporal patterns of offenders and offences (Boba, 2009; Bottoms & Wiles, 2002; Chainey & Ratcliffe, 2005; Siegel, 2001; Townsley, Tompson, & Sidebottom, 2008). The tripod of environmental criminology is constituted by: (a) routine activities theory, (b) rational choice theory, and (c) crime pattern theory. Rational choice theory sheds light on behavioral patterns of offenders and victims at the individual level. Crime pattern theory clarifies crime patterns at the social level, and routine activities theory discusses those patterns at the societal level (Boba, 2009). Each leg of this tripod is discussed below.

2.3.1.1 Routine activity theory

Devising the routine activity theory, L. E. Cohen and Felson (1979) explained changes in crime rates triggered by alterations in routine activity patterns. To L. E. Cohen and Felson, routine activities constitute a major part of human activities if occurs on a regular basis as part of daily life.[2] In addition, illegal activities are based on the rhythm, tempo and timing of legal daily routine activities of average people in societies. Thus, everyday routines relate to the risk and threat of criminal activities and victimization. According to routine activity theory, changes in employment (i.e. entry of women to work force), wealth (i.e. relative increase in wealth) and manufacturing (i.e. mass-production of electronic goods) have led to creation of more criminal opportunities for potential offenders and raised crime rates. Thus, according to L. E. Cohen and Felson predatory crime should not be only considered a sign of social breakdown but also a byproduct of freedom and wealth because any feature that opens an avenue for life enjoyment may simultaneously increase chances for *predatory violations*.

According to L. E. Cohen and Felson (1979), *direct-contact predatory violations* are dependent upon spatiotemporal convergence of three elements: (a) motivated offenders, (b) suitable targets and (c) guardian absence (p. 589). Not each and every offender can be considered a motivated offender. Offenders become specialized in certain types of criminal activities and avoid attacking every available target. Suitable targets may comprise of human beings as well as material assets. And guardians may include police officers, security guards, shopkeepers or CCTV systems.

[2] Routine activities may encompass any of the physiological, safety, belonging, esteem and seld-actualization needs of human beings as discussed by Maslow (1943).

Later, Clarke and Eck (2003) expanded minimal elements of *direct-contact predatory violations* concept (as devised by L. E. Cohen & Felson, 1979) and included handlers, guardians and managers as crime facilitators or preventers (See *Figure 1*). Handlers (i.e. family members, teachers, etc.) are individuals acquainted with offenders, and can influence or screen offenders' behavior. However, handlers may not necessarily inform law enforcement officers of delinquent behaviors of offenders. Guardians' roles may be compared to handlers in that while handlers might have some influence over potential offenders, guardians can keep an eye on people and remove them from crime-prone environments. Formal or informal guardianship can be reinforced by police officers and strengthened through acquaintanceship or friendship. Lastly, place managers (i.e. street stall owners, bus conductors or ticket clerks, etc.) have some responsibility or control over the use of place even though they might not be formally or fully in charge.

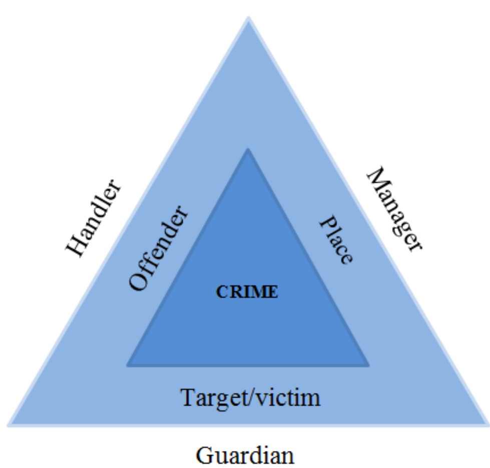

Figure 1. The crime triangle. From *Become a Problem-Solving Crime Analyst in 55 Steps*, by R. V. Clarke and J. E. Eck, 2003, London: Jill Dando Institute of Crime Science, University College London. Copyright (2003) by Jill Dando Institute of Crime Science. Reprinted with permission.

Lastly, according to the routine activity theory, suitable targets are valuable, visible, accessible and inertial (L. E. Cohen & Felson, 1979). Examining the records of stolen goods, Clarke (1999) suggested that stolen products are concealable, removable, available, valuable, enjoyable and disposable. Firstly, goods that cannot be easily concealed are more difficult to steal. Thus, large items may be less favored compared to small items. Secondly, products that are removable may have a higher probability of theft. Thirdly, offenders do not spend too much time searching for goods to steal. Therefore, visible goods take priority. Fourthly, value plays an important role in theft. Fifthly, enjoyable products are more at risk of theft. For instance, electronic goods are favored over other home appliances like kitchen utensils. Lastly, stolen merchandise will be used, traded or sold. Thus, items carrying identification signs may be less favored.

2.3.1.2 Rational choice theory

Criminals may decide to commit a crime when legal means of achieving goals or fulfilling desires are not available and as opportunities arise. According to rational choice theory (Clarke & Felson, 1993; Cornish & Clarke, 1986), most criminals assess the pros and cons of delinquent behaviors before committing an illegal act. This perception implies that engaging in criminal activities is (fairly) rational and mostly driven by offenders' perception of risks and anticipated rewards of the possible crime. Consequently, no crime will be committed when criminals anticipate high chances of being caught or small chances of reward.

Cornish and Clarke (1986) further discussed that involvement in criminal activities involves a long-term and a short-term decision; a long-term decision in the sense of becoming a criminal (crime involvement decision) and a short-term decision in the sense of taking advantage of opportunities (crime event decision). However, it has been argued that not all decisions are rational decisions. Many factors like alcohol abuse, drug usage and limited education among others may limit rationality. In brief, rational choice theory claims that through understanding behavioral patterns of offenders and their perception of risks and rewards, criminologists may develop better preventative measures for discouraging criminal activities (Clarke & Felson, 1993; Cornish & Clarke, 1986).

2.3.1.3 Crime pattern theory

P. L. Brantingham and P. J. Brantingham (1993) devised crime pattern theory to help explain crime patterns generated by interactions between offenders and targets in social and physical settings. Paul and Patricia Brantingham (1981b) identified four dimensions to criminal activities: (a) a legal dimension, (b) a victim dimension, (c) an offender dimension and (d) a spatial dimension. Therefore, crime is committed when a law is broken; someone or something is targeted; an illegal act is committed; and the offense takes place in space and time.

Crime pattern theory hypothesizes that crime is not randomly distributed in time and space, rather it is clustered and shaped by routine activities of offenders and victims (P. J. Brantingham & P. L. Brantingham, 1981b, 1984, 1993; P. L. Brantingham & P. J. Brantingham, 1993). Repetitive journeys to places of routine activities create a cognitive map[3] of traversed spaces for potential criminals and benevolent others. Awareness spaces are developed from

[3] Environmental image or cognitive map is a "result of a two-way process between the observer and his environment" (Lynch, 1964, p. 6), and is a representation of "the generalized mental picture of the exterior physical world that is held by an individual" (Lynch, 1964, p. 4).

activity spaces, are stored in people's brains and get restructured as people navigate in environment. However, awareness spaces have spatial and temporal limitations as people do not navigate in the entire urban setting and cannot be familiar with the entire urban environment.[4] Opportunity spaces exist unevenly inside activity spaces and criminal activities tend to occur where awareness spaces of criminals and opportunity spaces overlap (See *Figure 2*).

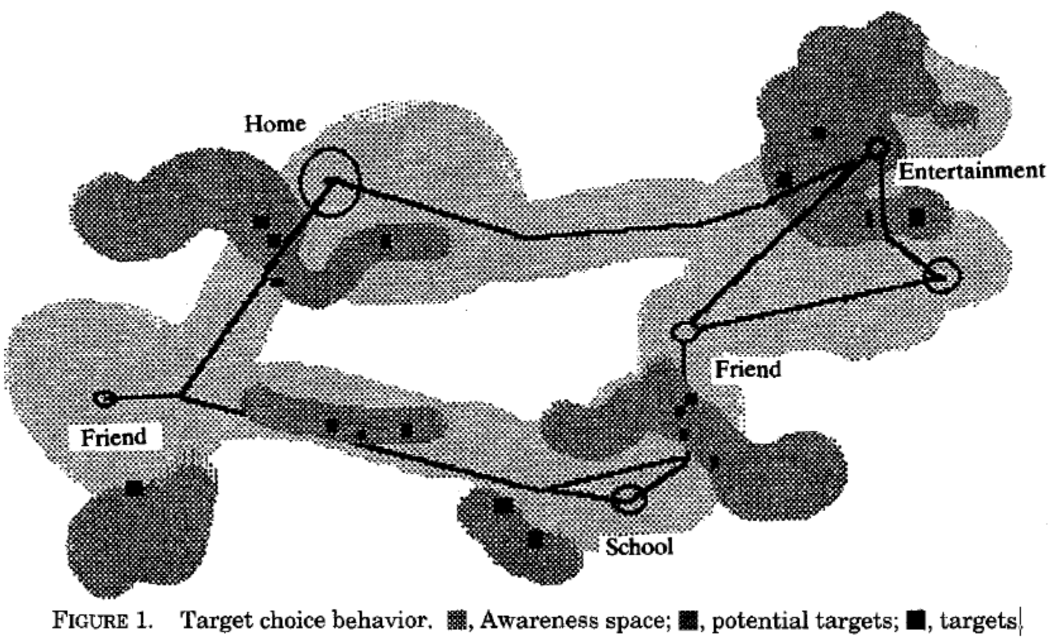

Figure 2. Target choice behavior. From "Nodes, Paths and Edges: Considerations on the Complexity of Crime and the Physical Environment," by P. L. Brantingham and P. J. Brantingham, 1993, *Journal of Environmental Psychology*, *13(1)*, p. 10. Copyright (1993) by Elsevier. Reprinted with permission.

Furthermore, P.J Brantingham and P. L. Brantingham (1981a, 1993) postulated that awareness spaces are governed by nodes, paths and edges. Grounded on seminal work of Kevin

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[4] Image of an environment or a given reality are susceptible to interpretation in eyes of different individuals. Immediate sensation or former experiences might play a part in the formation of environmental image. Research has also shown a strong correlation between an individual's image of macro and micro environments and the physical settings themselves. Some other factors like age, race, sex and socioeconomic status among others can influence the accuracy and detail of cognitive maps (Downs & Stea, 1973; Schneider & Kitchen, 2007).

Lynch (1964)[5], Paul and Patricia Brantingham (1993) discussed nodes (i.e. home, work, etc.) as places where individuals are drawn to perform their routine activities. Thus, nodes provide ample opportunities for criminal deeds. Paths (i.e. streets, sidewalks, etc.) connect activity nodes and potential criminals may notice opportunities as they move along these links. Lastly, physical or perceptual edges (i.e. neighborhood borders, etc.) split the cityscape. Thus, criminal opportunities may arise in proximity edges as strangers do not stand out and appear out of place in bordering areas.

In sum, according to the crime pattern theory (P. L. Brantingham & P. J. Brantingham, 1993), patterns of crime are comprehendible through the juxtaposition of processes of the criminal events, the offender's interpretation of suitable targets, routine activities of offenders and victims, readiness and willingness of offenders and the environmental backcloth[6] (pp. 266-276). Thus, crime pattern theory can be considered as a convergence of routine activities and rational choice theory by bringing together "offender spatial distribution and offences spatial distribution" together (Chainey & Ratcliffe, 2005).

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[5] Lynch (1964) set the groundwork in studying which urban elements constitute citizens' spatial image of a city. Interviewing and linking residents' verbal answers and sketches from Boston, New Jersey and Los Angeles, Lynch proposed that the image of a city is composed of five significant elements: paths, landmarks, edges, nodes and districts. Paths were ranked as the most frequent element to be mentioned by citizens followed by landmarks, nodes, districts and edges. According to Lynch, paths steer residents' movements; edges border different areas; districts subdivide cities into smaller divisions; nodes are junctures or cores; and landmarks are recognizable elements in the cityscape.

[6] Backcloth is a term used for the variable-ever changing context that surrounds the daily lives of individuals (P. L. Brantingham & P. J. Brantingham, 1993).

2.3.2 Situational crime prevention

Crime is considered contextual and opportunistic, and situational crime prevention is concentrated on modifying the built environment to reduce the likelihood of crime occurrence (Tonry & Farrington, 1995). Comprising a theoretical framework, a methodology and a set of established techniques, situational crime prevention intends to manipulate difficulties, risks and rewards of criminal activities. Escalating perceived risks of detection or detention, increasing efforts involved in conducting criminal activities and decreasing anticipated rewards of certain crimes comprise the main tenets of situational crime prevention (Clarke, 1995; Tonry & Farrington, 1995). Theoretically, situational crime prevention is grounded on rational choice and routine activities theory. Methodologically, it employs an action research approach, and technically, places great reliance on products and technological advancements for preventing and deterring crime through 12 opportunity-reducing techniques or countermeasures shown in *Figure 3* (Clarke, 1995).

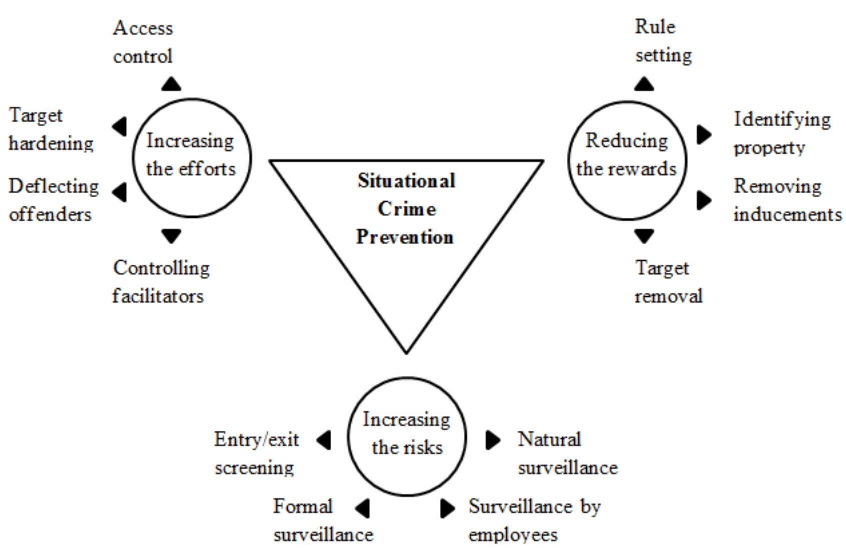

Figure 3. Situational crime prevention and its countermeasures (Source: Author).

Displacement of crimes and diffusion of benefits are two critical topics addressed by critics and advocates of situational crime prevention. Displacement of crime is discussed "as the unintended increase in crime following the introduction of crime reduction scheme" (Welsh & Farrington, 2009, p. 54). According to Reppetto (1976), crime displacement may happen in five forms: (a) temporal (conversion in time), (b) tactical (conversion in tactics), (c) target (conversion of suitable victims), (d) territorial (conversion of place) and (e) functional (conversion of crime type). Diffusion of benefits is the reverse form of displacement and is discussed "as the unintended decrease in nontargeted crimes following from a crime reduction scheme" (Welsh & Farrington, 2009, p. 55). However, it is controversial as to what extent implementation of situational crime prevention countermeasures may displace crimes or diffuse benefits.

There is an overlap between some countermeasures of situational crime prevention shown in *Figure 3* and principles of crime prevention through environmental design shown in *Figure 4*. However, in contrast to crime prevention through environmental design which great importance is placed on physical design of built environments, situational crime prevention places great reliance on products and technological advancements for crime prevention and deterrence.

2.3.3 Crime prevention through environmental design (CPTED)

The term crime prevention through environmental design (CPTED), was coined by Jeffry (1977). Jeffry among others proposed some strategies for preventing crime through strategic design of the built environment. According to this concept, "… the proper design and effective use of the built environment can lead to a reduction in the fear and incidence of crime, and improvement in the quality of life" (Crowe, 2000, p. 46 as cited in Cozens et al., 2005, p. 329). In a review of classical (Katyal, 2002) and contemporary bibliographies (Cozens et al., 2005), Katyal and Cozens et al. discussed the physical concepts of CPTED and explored how architecture (building design, urban studies and planning) may prevent crime through practical applications of territoriality, surveillance, target hardening, access control, activity support and maintenance (See *Figure 4*). CPTED is now claimed to extend beyond physical factors and to encompass socio-cultural dynamics to deter crime from emergence (Saville & Cleveland, 2003a, 2003b). Physical concepts of CPTED are discussed below and shown in *Figure 4*.

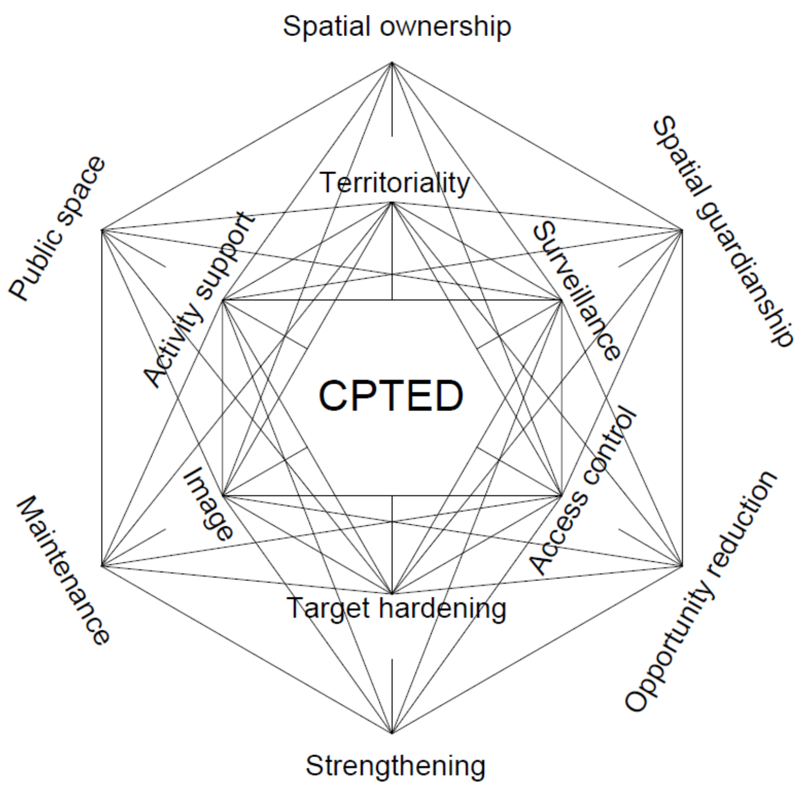

Figure 4: Crime prevention through environmental design and its concepts (Source: Author).

1. Territoriality reinforces the notion of spatial ownership. Territoriality may reduce crime by discouraging illegitimate users from trespassing private spaces. Territoriality can be promoted through symbolic and real barriers. Real territorial barriers may include installation of fencing or use of locked doors. Symbolic territorial barriers may range from building a series of steps to construction of archways or from public-private differentiation by color and texture to installation of signage and artwork. Other territorial techniques such as limiting the number of individuals sharing common areas (i.e. entrances, staircases, etc.), installing monuments or designing streetscapes may also enhance the sense of territoriality (Cozens et al., 2005; Katyal, 2002).

Studies have explored how communicating spatial ownership through real or symbolic barriers can increase sense of intrusion in offenders' eye and decrease chances of victimization (Armitage, 2007; Brown & Altman, 1983; Brown & Bentley, 1993). Nevertheless, territoriality has been widely criticized because of its definition, interpretation and measurement. In addition, it has been claimed that territoriality can be highly influenced by space, society and culture (Cozens et al., 2005).

2. Surveillance promotes the notion of spatial guardianship. Surveillance is discussed under three categories of: (a) natural/informal surveillance (i.e. through improving building design, etc.), (b) organized/formal surveillance (i.e. by police officers, shopkeepers, etc.) and (c) mechanical surveillance (i.e. through lighting and CCTV systems) (Cozens et al., 2005; Katyal, 2002).

Research has shown inverse relationships between the degree of natural surveillance and residential burglary incidents (Bellair, 2000; Coupe & Blake, 2006; Van Nes & López, 2010). In addition, studies have revealed offenders avoid properties with greater degrees of natural surveillance (Coupe & Blake, 2006; Sorensen, 2003; Wilcox, Madensen, & Tillyer, 2007).

Formal surveillance has shown to reduce car-related crime in parking lots (Barclay, Buckley, Brantingham, Brantingham, & Whinn-Yates, 1996; Laycock & Austin, 1992; Poyner, 1991), to decrease shoplifting in the retail industry (Kajalo & Lindblom, 2011; Lindblom & Kajalo, 2011) and to prevent bank robberies (Clarke, Field, & McGrath, 1991; Hannan, 1982).

Installation of CCTV in public places has been revealed to deter vandalism and robbery (for a review see Welsh & Farrington, 2009), and lighting improvement has shown to reduce crime and fear of crime (Cozens, Neale, Whitaker, Hillier, & Graham, 2003; Farrington & Welsh, 2002; Welsh & Farrington, 2009).

Informal and formal modes of surveillance play more of a background role compared to mechanical types of surveillance in surveillance-crime studies (Cozens et al., 2005; Newman, 1973). Even though informal, formal and mechanical types of surveillance are intended to deter crime through detectability enhancements, critics of this concept claim that the ability to survey does not necessarily mean that surveillance is routinely taking place.

3. Access control supports the notion of opportunity reduction. Access control is discussed under three forms of: (a) natural/informal control (i.e. spatial opportunities), (b) organized/formal control (i.e. security personnel) and (c) mechanical control (i.e. locks, bolts) (Cozens et al., 2005; Katyal, 2002).

Extremely controversial results were found for opportunity reduction through target control strategies. For instance, while Atlas and Le Blanc (1994) found no significant reduction in the number of recorded robberies and assaults after introduction of road closure, Newman (1996) and Matthews (1992) among others found significant reductions in the number of criminal activities after implementation of road closure.

4. Activity support encourages usage of public space. This notion has also been claimed to bring communities together and build social communities (Cozens et al., 2005; Katyal, 2002).

A growing body of research on mixed-used developments suggests that increasing the range of activities in spatial and temporal terms can reduce criminal opportunities (Pettersson, 1997; Poyner, 2006). However, some other research suggests that the relationship between crime and mix-use developments are curvilinear (Browning et al., 2010) or inverse (McCord, Ratcliffe, Garcia, & Taylor, 2007). There is also an ongoing effort to understand human movement and its relation to patterns of criminal activities (Cozens et al., 2005; Hillier, 2004).

5. Image underlies the notion of maintenance. This notion mainly refers to physical conditions of the built environment (Cozens et al., 2005).

The significance of well-maintained environments in deterring crime has long been acknowledged. Much research indicates that crime can be significantly reduced by routine maintenance of the urban environment (Cozens, Hillier, & Prescott, 2001; Hirschfield, Newton, & Rogerson, 2010; Ross & Jang, 2000; Wilson & Kelling, 1982).

6. Target hardening endorses the notion of strengthening. Target hardening is the oldest established tactic to crime deterrence. Noticeable (i.e. strategic placement of entryways and emergency exists) or imperceptible techniques (i.e. usage of graffiti-resistant paints or installation of steel core doors) may be used for strengthening potential targets (Cozens et al., 2005; Katyal, 2002).

Research has shown residential security measures (i.e. window guards, alarm systems, locks, etc.) can reduce the risk burglary victimization (Budd, 1999; Tseloni, Wittebrood, & Farrell, 2004). However, critics of this notion claim that target hardening strategies may lead to mental fortifications of residents behind physical barriers leading to withdrawal of residents from monitoring and maintaining their neighborhood of residence (Cozens et al., 2005).

In sum, even though CPTED principles have shown to be effective in deterring crime in some settings, debates still exist on key concepts of CPTED, prioritization of its concepts and applicability of its principles in a broad range of environments. In addition, it has been argued that firstly, CPTED concepts are less likely to deter intoxicated offenders. Secondly, social, economic and demographic factors may greatly influence effectiveness of CPTED strategies. Thirdly, displacement can be a major issue in applicability of CPTED principles. Lastly, threshold of neighborhoods to handle incivilities is different (Cozens et al., 2005; Katyal, 2002).

Thus, a broader and methodology more rigorous evaluation of CPTED principles along with community involvement is desired in order to understand how CPTED concepts work, where CPTED concepts work best and how implications of CPTED concepts could be evaluated (Tonry & Farrington, 1995; Welsh & Farrington, 2005). In this study, I concentrate on one of the least studied and understood principle of CPTED - natural surveillance. This following section reviews the key findings of researchers who developed or built upon the notion of natural surveillance.

2.3.3.1 Emergence of the notion of natural/informal surveillance

The concept of natural surveillance was first discussed by Jane Jacobs (1961). Later Oscar Newman (1973) built on Jacobs' notion of natural surveillance and applied this notion to the design of low-income and middle-income housing layouts. The following paragraphs are devoted to a discussion of Jane Jacobs' notion of *eyes upon the street* and Oscar Newman's concept of *defensible space*. Later a comparison is drawn between how Jacobs and Newman approached defined community safety.

2.3.3.1.1 Eyes upon the street

Jane Jacobs (1961), a perceptive ethnographer (Gans, 2006), in her seminal reading *The Death and Life of Great American Cities* discussed (a) the essential role of sidewalks in creating livable environments, (b) the importance of density and diversity in urban layouts, (c) the forces that control cities' vitality and (4) the importance of urban diversity. Jacobs concluded with some suggestions for planning and administrative practices.

Jacobs (1961) postulated that cities are safe from barbarism and fear of barbarism if their streets are safe from incivility and fear of incivility. For Jacobs, streets and sidewalks are the main constituents of urban layouts, and thereby play a central role in the safety and attractiveness of cities. Jacobs hypothesized that constant use of sidewalks assures safety, brings people together and assimilates children. This attractiveness and safety is enforced and influenced through constant sidewalk users, bordering land uses and diversity. Mixed primary uses, short blocks, reasonable mix of old and new buildings and density are thereby discussed as primary constituents of livable cities.

> The bedrock attribute of a successful city district is that a person must feel personally safe and secure on the street among all these strangers. He must not feel automatically menaced by them. A city district that fails in this respect also does badly in other ways and lays up for itself, and for its city at large, mountain on mountain of trouble. (Jacobs, 1961, p. 30)

Providing examples from Boston and New York City, Jacobs (1961) hypothesized that some street segments provide more opportunities for crime incidents than others. Jacobs sought to answer: what are the must-have qualities of streets that might play a part in the drama of civilization versus barbarism? For Jacobs, well-used streets are characterized by three main qualities (p. 35):

1. Public and private spaces are clearly demarcated and do not blend into one another.
2. Buildings are outward looking, oriented toward streets to ensure there are eyes upon streets watching strangers and other residents. Eyes of natural dwellers of streets (natural proprietors) not only keep eyes on strangers but also assure safety for other residents and strangers.
3. Sidewalks have constant users to encourage residents to watch sidewalks. Further, by having more sidewalk users the notion of eyes upon the street can be expanded to eyes of the dwellers along streets and eyes of the constant flow of strangers along sidewalks.

Therefore, for Jacobs (1961) safety is insured in *eye-policed* streets and fear rules in *blind-eyed* segments. Jacobs further explained that once a clear demarcation between public and private space is set, and eyes of natural proprietors survey the ongoing activities of streets, then sidewalk users may not be able to impose harm on residents. Jacobs (1961) further discussed natural surveillance through three principles: diversity, building design and lighting.

1. According to Jacobs (1961), surveillance or natural policing is not feasible without providing people with ample reasons for using or watching sidewalks on a constant basis. Small stores, entertainment opportunities or public and semi-public spaces encourage people to walk and make street segments more traversed.

   In addition, storekeepers and small business owners are peace advocates and can add to the number of effective eyes on the street if placed in adequate numbers and at appropriate distance from one another. In addition, activities generated by people attract more people. People like watching other people and livable streets have their users and their pure watchers.

2. Natural surveillance through building design can be enhanced by placing windows and balconies toward public spaces and avoiding inward looking enclaves.
3. Last but not least, lighting can increase visual perception and reduce crime and fear of crime during nighttime hours. However, according to Jacobs (1961) increasing the power of perception through lighting without having eyes upon the street might be meaningless.

Nevertheless, three approaches have been taken by city residents in regard to unsafe urban environments. Firstly, fleeing into suburbs, upper and upper-middle class population have let incivility rule in low-income and some middle-income quarters with unfortunate populations being trapped within these areas. Secondly, people have taken refuge from incivility in vehicles (mostly private) and endure in automobiles until destinations are reached. Lastly, many citizens have ignored cities being split into Turfs through literal or figurative fences, and have left police forces to deal with concerns of these gray segments (Jacobs, 1961, pp. 46-47).

Jacobs (1961) concluded with two main points; firstly, that fleeing to suburbs and trading off suburban contexts with urban settings won't solve safety issues in urban environments. Secondly, safety cannot be assured by police force but by active roles of residents for the common good. According to Ranasinghe (2012), Jacobs made a distinction between the concepts of policing and police force claiming that policing is not necessarily achievable through police (Ranasinghe, 2012). While police force refers to recruitment of civil force for maintaining public order, according to Jacobs, policing can be realized through natural surveillance and informal networks among residents. However, unsafe cities have been deliberately or unintentionally built and designed and city residents are left with no choice but to adapt themselves to leave them or live within them.

2.3.3.1.2 Defensible space

In coining the term *Defensible Space*, Newman (1973) addressed what elements of physical design can help inhabitants bring their surrounding environment under control, and also how social fabric can be translated into the physical design of residential neighborhoods, enabling inhabitants to defend themselves from criminal events. Newman defined defensible space as:

> A model for residential environments which inhibits crime by creating the physical expression of a social fabric that defends itself. All the different elements which combine to make a defensible space have a common goal-an environment in which latent territoriality and sense of community in the inhabitants can be translated into responsibility for insuring a safe, productive, and well-maintained living space. (Newman, 1973, p. 3)

> A surrogate term for the range of mechanisms-real and symbolic barriers, strongly defined areas of influence, and improved opportunities for surveillance- that combine to bring an environment under the control of its residents. (Newman, 1973, p. 3)

Newman (1973) discussed defensible space through four main categories of: (a) territoriality, (b) surveillance, (c) image and (d) milieu. According to Newman, residential neighborhoods should be separated into zones where residents' area of influence is symbolically or actually separated. Non-private areas of residential environments should be naturally surveyed. Configuration of buildings should not be distinct from their immediate environment, isolating or conveying vulnerability or prosperity of occupants. Finally, neighborhoods should not be diverse meaning that facilities that provide threats to residential environments should not be incorporated into the design of residential quarters.

The first concept of defensible space - territoriality is "the capacity of the physical environment to create perceived zones of territorial influences" (Newman, 1973, p. 51). Historically, single-family houses were separated from their neighbors by as little as six feet. Over time, fences, shrubs, walls or gates created a clear demarcation between residential dwellings, their adjacent neighbors and public open spaces. However, residency in denser agglomerations created difficulties for implicit or explicit demarcation of territoriality, and provided fewer opportunities for self-assertion, collective identification or territorial association.

According to Newman and colleagues (1973), proper exterior site planning and interior building design can help strengthen territorial feelings in high-density low-income or middle-income residential agglomerations. The following mechanisms were advised by advocates of defensible space theory for parsing dense residential clusters into territorial identifiable subzones (Newman, 1973, pp. 53-77):

- Subdividing residential developments to outline individual building's area of influence.
- Creating a hierarchical transition between public and private spaces.
- Subdividing building interiors to define area of influence of apartment units or clusters.
- Limiting the number of apartment units clustered together.
- Integrating amenities and facilities (i.e. playground, sitting areas, and washer-dryer facilities) within inhabitants' area of influence.

The second defensible space concept- surveillance, is discussed as "the capacity of physical design to provide surveillance opportunities for residents and their agents" (Newman, 1973, p. 78). Conveying a feeling that one is constantly under observation not only discourages occurrence of nonviolent activities but also decreases irrational fear associated with it. Subsequently, feeling safe in neighborhoods will have a multiplier effect on encouraging residents to use non-private areas of their residential quarters and on improving safety and feeling of safety in neighborhoods.

However, Newman (1973) claimed that increasing surveillance opportunities without providing territorial cues cannot effectively reduce or impede delinquent behavior or criminal activities. Several mechanisms were introduced and applied in the design of low- and middle-income housing layouts to enhance surveillance opportunities for residents and guardians. These mechanisms are outlined below (Newman, 1973, pp. 80-101):

- Non-private areas and access paths to residential developments should be continuously surveyed. Buildings ought to be designed inward and outward looking and paths should have ample lighting.
- Activity spaces in residential dwellings should be deigned to facilitate constant natural surveillance of exterior spaces.
- Ambiguities in the design of public and private spaces should be minimized and legibility of residential developments should be maximized.

Lastly, image and milieu are defined as "the capacity of design to influence the perception of a project's uniqueness, isolation and stigma" (Newman, 1973, p. 102). Developments offering distinct look to certain dwellings, publicly-assisted housing or low-income developments may invite extra attention and increase risk of victimization. According to Newman (1973), the following mechanisms may increase vulnerability of residences to criminal activities (pp. 103-117):

- Interventions in urban circulation patterns, specifically closing off street segments.
- Creating distinctiveness in exterior appearance of buildings in existing urban settings.
- Creating dissimilarities in interior finishing of new developments.
- Portrayal of life style in the design of residential dwellings.

- Diversity or integration of institutional, commercial, industrial and entertainment facilities in residential settings. Newman considered bars, high schools and junior colleges as facilities that may cause threat to the milieu of residential environment.

2.3.3.1.3 Eyes upon the street versus defensible space

Jacobs and Newman approached social concerns of cities taking different outlooks and scales. Newman studied how the design of low-income and middle-income residential neighborhoods correlates to victimization rate. Jacobs took a larger view and explored socio-spatial concerns of cities and introduced some principles for city planning.

Jacobs and Newman both claimed that crime cannot be fought by police force and gun power, rather communities should act cohesively to keep crime in control and to support police enforcement. They also postulated that fleeing to suburbs or seeking safety in guarded semi-luxury or luxury dwellings degrades the traditional responsibility of citizenry and causes physical and mental withdrawal from society. In addition, low-income or moderate-income persons who can neither afford to be in suburban areas nor in guarded dwellings are left alone to fight for secure and crime-free environments.

Taking into account building design, Jacobs and Newman share similar ideas on demarcating public and private spaces, planning outward looking developments and providing surveillance through strategic placement of windows and balconies. However, similar thoughts were not shared on the role of strangers, non-residential facilities and diversity in residential environments. In contrast to Jacobs who is welcoming of strangers, Newman was skeptical about the role that strangers might play in safety and security of neighborhoods.

Further, Jacobs supported diversity or integration of commercial and entertainment facilities within the service area of residential developments and claimed that not only residents but also service providers can benefit from this integration. However, Newman claimed that placing non-residential uses in residential areas demands further understanding of the nature of businesses, their users and their activity period among other factors. Lastly, according to Jacobs a mixture of new and old buildings is one of the features of city diversity. Concerns may arise if old developments are vacated, not properly restored or used. However, Newman was not welcoming of dissimilarities that may arise between new and old developments (See Table 1).

Table 1

Jacobs' notion of eyes upon the street versus Newman's notion of defensible space (Source: Author).

Scholars	Theories	Categories	Descriptions
Jacobs (1961)	Eyes upon the street	Territoriality	Demarcation between public and private Constant sidewalk users are desirable
		Surveillance	Natural surveillance through windows Outward looking designs Street lighting
		Image	Appropriate proportion of old and new buildings
		Diversity	Amenities and facilities are welcome
Newman (1973)	Defensible space	Territoriality	Subdivision of public and private spaces Predominance of community residents is desired
		Surveillance	Natural surveillance through windows Activity spaces should face streets
		Image	No distinction between developments
		Milieu	Amenities and facilities are not welcome

2.4 Natural Surveillance and Residential Burglaries

This section offers examples on how natural surveillance has been measured and its relationship to residential burglaries is studied. This review is divided into six parts. The first section discusses risk factors associated with residential burglaries. The second part seeks to understand the relationship between spatial characteristics of dwellings (as measured by field observations) and chances of residential burglaries. The third part explores how burglars, officers and residents view the vulnerability of dwellings to burglary. The fourth section seeks to apprehend residents' perspectives on the reciprocity between natural surveillance and residential burglaries. The fifth part reviews studies that associated syntactical measures of space to burglary victimization. And the last section looks into the relationship between landscape features and burglary rates. I conclude this section by highlighting the strengths and weaknesses of each approach and introducing new avenues for measuring natural surveillance.

2.4.1 Risk factors associated with burglaries

Brown and Altman (1981) conceptualized a model for the sequential decision-making process of burglaries and presented a number of environmental factors that may play a part in the process of burglaries. Detectability, actual and symbolic barriers, traces of occupancy and social climate at three levels of street, parcel and home were hypothesized to influence burglary decisions. Detectability at the street, site and house level was assumed to be affected by placement of building openings, architectural design and placement of landscape features among other factors (See Table 2).

Table 2

Vulnerability factors associated with street, site and house. From Territoriality and residential crime: A conceptual framework (p.68), by B. B. Brown and I. Altman, in *Environmental Criminology*, by P. J. Brantingham and P. L. Brantingham (Eds.), 1981, Beverly Hills, CA: Sage Publications. Copyright (1981) by Sage Publications. Reprinted with permission.

TABLE 2.2 Vulnerability Factors Associated with Street, Site, and House

Factor	*Street*	*Site*	*House*
Detectability	Design: winding vs. narrow Distance: street to house Lighting Window, door positions relative to street Textural composition of road Weather: snow, ice, rain	Shrubs, trees, walls, fences blocking burglar from street or house Burglar seeing into house–door and window position, covering (blinds or curtains) Auditory cues–squeaky gate, dogs barking, sidewalk texture	Target window visibility to neighbors, street Window positioned to see returning occupants once inside General visibility by neighbors or others due to window placement
Actual Barriers	Locked gates, fences, guards	Locked gates, fences, guards Is opening large enough to carry away goods?	Locks on windows, door–degree of difficulty or time to open Alarm system Is opening large enough to carry away goods?
Symbolic Barriers	Welcome signs Neighborhood Assoc. Signs Distinctive cultivation for streets	Distinctive personalizing items in yard--mail boxes, lampposts, welcome mats, signs, flower garden Marking of entryway from the public street (sidewalks, raised or lowered elevation, paths)	Nameplate, coat of arms on door Signs on door (no solicitors Neighborhood Watch) Distinctive coloring or material of house

Weisel (2002) and Sorensen (2003) explored risk factors associated with single-family residential burglaries and provided situational crime prevention approaches for burglary prevention and reduction. Visibility or surveillability is identified as one of the main factors of burglary victimization. According to Weisel and Sorensen, secluded or corner buildings, poorly-lighted buildings and obstructed buildings and building openings are more likely than others to be targeted by burglars (See Table 3).

Table 3

Measures of surveillability quoting Weisel and Sorensen, tabulated by the author.

Surveillability	Description of measures
Surveillability to neighbors or passers-by (Sorensen, 2003)	(1) "Houses with high fences or thick trees or shrubbery *(p. 18).* (2) "Houses in isolated areas" *(p. 18).* (3) "Houses set back from the road" *(p. 18).* (4) "Houses with low levels of night-time lighting" *(p. 18).* (5) "Houses on large plots of land next to parks or other non-residential areas" *(p. 18).* (6) "Houses on corners" *(p. 18).*
Surveillability to neighbors or passers-by (Weisel, 2002)	(1) "Houses with cover" *(p. 9).* (2) "Houses that are secluded" *(p. 10).* (3) "Houses with poor lighting" *(p. 10).* (4) "Houses on corners" *(p. 11).* (5) "Houses with concealing architectural designs" *(p. 11).*

2.4.2 Observation studies of dwelling characteristics and burglaries

Brown and Altman (1983) compared burglarized dwellings located on burglarized blocks, non-burglarized dwellings located on burglarized blocks and non-burglarized dwellings located on non-burglarized blocks to understand whether they differ in terms of symbolic barriers, actual barriers, detectability, traces of occupancy and social climate. Dwellings were rated on 215 measures in the season and time during which burglaries took place. Factor analysis showed that the 215-item rating instrument could be presented by 14 main variables shown in

Table 4. Detectability was measured by the degree building facades can be viewed, the degree neighboring houses can be viewed and availability of lighting on yard. Results of discriminant analysis and multiple regression revealed non-burglarized dwellings on non-burglarized blocks presented more symbolic territorial signs of ownership at the lot and street level (symbolic barriers), had yard fencing present (actual barriers), presented more traces of tenancy and had a garage on lot (traces of occupancy) and could be more surveyed by immediate neighbors (detectability).

Table 4

Composite scores of the five dependent variable clusters by house type. From "Territoriality, Defensible Space and Residential Burglary: An Environmental Analysis," by B. B. Brown and I. Altman, 1983, *Journal of Environmental Psychology*, *3*, p. 209, Copyright (1983) by Elsevier. Reprinted with permission.

TABLE 1

Composite scores of the five dependent variable clusters by house type

Variable class	House type*		
Composite number and description	Burg	Non-burg-bb	Non-burg-nbb
Symbolic barriers			
1. Street signs	0·048	0·031	−0·075
2. Territorial borders	−0·064	−0·103	0·167
3. Altitude	−0·002	−0·037	0·039
4. Identity markers	−0·053	−0·006	0·058
Actual barriers			
5. Yard barriers	−0·062	0·100	0·097
Traces			
6. Garage	−0·170	0·061	0·120
7. People seen on street	−0·037	0·024	0·013
8. People seen in yards	−0·074	−0·019	0·091
9. Parked cars seen	−0·028	−0·075	0·104
12. Traces of presence†	−0·052	−0·014	0·070
13. Traces of absence†	0·046	0·023	−0·059
14. Neighbors seen†	−0·072	−0·011	0·076
15. Traces of public use†	0·056	0·007	−0·063
Detectability			
10. House visibility-front	−0·013	−0·050	0·063
11. General visibility	0·058	−0·024	−0·035
12. House visibility-right	0·040	−0·023	−0·015
19. Adjacent houses seen†	−0·112	0·037	0·076
20. Site lighting	−0·074	0·033	0·039
Social climate			
13. Public buildings	0·003	−0·034	0·020
14. Neighbor reactions	−0·044	0·020	0·018

Note. All composite scores are means computed from the individual variable means after they have been converted to *z* scores.
* Burg = burglarized house, Non-burg-bb = non-burglarized house on a burglarized block, Non-burg-nbb = non-burglarized house on a non-burglarized block.
† As explained in the text, 'variables' 15–20 are actually subscales created after the factor analysis; therefore, these variables are out of sequential order.

In another study, Coupe and Blake (2006) investigated the relationship between residential burglaries and natural surveillance in a conurbation[7] in England. A stratified sample was chosen from the reported burglaries taken place in 1994 and data were collected from police reports, victims' interview questionnaires, site surveys and census data. Natural surveillance was studied through two measures, target suitability and target exposure and rated by three surveyors (See Table 5).

Target suitability was measured through the degree of visibility and distance of burglarized buildings to adjacent buildings and roads, and the ease of access or regress from rear side of buildings. Target exposure was measured though the degree barrier or landscape features conceal burglarized buildings and the number and distance of visible buildings from and to the burglarized buildings.

Statistically significant results were found between time of offence, occupancy, visibility and chances of being burglarized. During the day, properties in richer neighborhoods with denser front covers were considered suitable targets, rather during the night hours townhouses with less cover were suitable burglary targets. In addition, the front door was the most common means of entry during the daylight and rear windows were preferred during the nighttime hours.

[7] Conurbation is an extensive urban area resulting from expansion of several cities so that they coalesce but usually retain their separate entities.

Table 5

Measures of surveillability quoting Coupe and Blake, tabulated by the author.

Surveillability	Description of measures
Target suitability	(1) "Situation of burgled dwellings with respect to neighboring houses" *(p. 436)*. (2) "Ease of rear access" *(p. 436)*. (3) "Distance from other properties and the road" *(p. 436)*.
Target exposure	(1) "The number of properties visible to and from target dwellings" *(p. 436)*. (2) "The estimated distance from properties visible to and from target dwellings" *(p. 436)*. (3) "The cover surrounding the dwelling" *(p. 436)*.

Wilcox, Madensen and Tillyer (2007) investigated the relationship between burglary incidents and physical (target hardening), personal (home occupancy), social (informal control), and natural (surveillance) dimensions of guardianship at the dwelling and neighborhood-level. The degree of natural surveillance was an index developed from eight measures: (1) provision of windows on ground floors, (2) presence of fencing around buildings, (3) an adjacent empty lot, (4) being a corner lot, (5) facing a back alley, (6) facing a two-way street on front, (7) concealment of the front door with vegetation and (8) building use (See Table 6). Results of hierarchical logistic modeling (HLM) showed that dwellings with higher indices of natural surveillance are significantly less likely to be burglarized.

Table 6

Measures of surveillability quoting Wilcox, Madensen and Tillyer, tabulated by the author.

Surveillability	Description of measures
Informal surveillance	(1) "Ground floor windows" *(p. 782)*. (2) "Tall fence/hedge around the dwelling" *(p. 782)*. (3) "An empty lot next door" *(p. 782)*. (4) "A corner lot" *(p. 782)*. (5) "An alley behind the home" *(p. 782)*. (6) "A two way (as opposed to one-way or dead-end) street" *(p. 782)*. (7) "Trees/shrubs blocking the front door" *(p. 782)*. (8) "Multiple units within the dwelling" *(p. 782)*.

Carrying out interviews and day time observations in 181 street segments comprising of 2,847 properties in The Hague, NL, Reynald (2011a) explored what spatio-physical and socio-demographic factors influence guardianship intensity, and the relationship between guardianship intensity and property crime at two levels of building and street segment. Natural surveillance, as one of the significant physical predictors of guardianship, was rated on a 4-point scale and measured through observing the extent to which windows can survey public areas (See Table 7). Employing regressions, significant inverse relations were observed between property crime and guardianship intensity, street maintenance and distance to downtown. In addition, the relationship between target hardening, territoriality, mixed use developments and property crime was shown to be direct.

Table 7

Measures of surveillability quoting Reynald, tabulated by the author.

Surveillability	Description of measures
Guardianship Intensity	(1) "The property was occupied or not" *(p. 121).* (2) "The occupant was monitoring or not" *(p. 122).* (3) "The occupant intervened directly by inquiring about the observers' presence on the street" *(p. 122).*
Natural surveillance	(1) "The extent to which the view of public space from property windows was obstructed" *(p. 123).*

Foster, Giles-Corti and Knuiman (2011) studied the relationship between housing layouts and physical incivilities in a suburban neighborhood in Perth, Australia.[8] A team of three surveys walked in street segments on weekdays and rated buildings according to features assumed to encourage natural surveillance and to echo territoriality shown in Table 8. Dichotomous variables were later developed for study variables, for instance the degree of natural surveillance was dichotomized by less/more degrees of road visibility, presence/absence of a verandah, porch or balcony, presence/absence of front double garages and less/more public-private demarcation.

The results of univariate and multivariate analyses revealed that after controlling for number of parcels, clustering in residential layouts and value of lots, the likelihood of finding disorder significantly decreased with at least one dwelling on block face having a verandah, porch or balcony, or with presentence of fencing that does not obstruct visibility. On the contrary, that likelihood significantly increased by presence of at least one vacant lot on street segments. Further, the results of univariate analysis showed that the likelihood of finding graffiti significantly increases when front windows of at least one house are secured with bars or at least

[8] The purpose of this research was to study the relationship between housing layout and existence of graffiti and disorder but we included this study because graffiti and disorder have a spatial visibility component.

one house has unattended front yard, while multivariate analysis suggested that the likelihood of observing graffiti significantly increases by at least one house having unkempt front garden on street segment. In addition, according to Foster, et al., the log odds of incivilities decreases more noticeably by the cumulative existence of physical design elements rather than presence of a couple of elements.

Table 8

Inter-rater reliability of study variables pertaining to street segments. From "Creating Safe Walkable Streetscapes: Does House Design and Upkeep Discourage Incivilities in Suburban Neighborhoods?," by S. Foster, B. Giles-Corti and M. Knuiman, 2011, *Journal of Environmental Psychology*, *31*, p. 82, Copyright (2011) by Elsevier. Reprinted with permission.

Table 1
Inter-rater reliability of study variables pertaining to street segments ($n = 69$).

Characteristic	Kappa
Independent variables (house characteristics)	
Houses with good visibility from the street (i.e., windows are clearly visible from street)	0.65
Houses with front verandah, porch or balcony	0.76
Houses with double garages doors fronting the street	0.85
Houses with a high solid front wall	0.97
Houses with a low front wall, fence, hedge or border marking the property	0.76
Houses with outdoor furniture in the front yard, verandah, porch or balcony	0.76
Houses with personalised decoration (e.g., garden ornaments, name plate)	0.65
Houses with security bars, grills or roller shutters on front windows	0.88
Houses with unkempt front lawns	0.43
Houses with unkempt front gardens or no garden at all	0.62
Vacant lots	0.94
Houses under construction	0.74
Dependent variables (street characteristics)	
Disorder	0.65
Graffiti	0.80

2.4.3 Vulnerability of dwellings to burglary risk

Police officers, residents of communities and burglars are involved in the process and aftermath of criminal activities. These groups may share different views on vulnerability of dwellings to burglary risk; however their perspectives provide valuable information for CPTED programs and practices.

Nee and Meenaghan (2006) interviewed 50 incarcerated burglars in England to investigate whether burglars follow an impulsive, premeditated or sequential decision making strategy and what environmental cues are central in burglars eyes for target appraisal and selection. The results revealed that burglars go through a sequential searching strategy rather than an impulsive or a planned one. In addition, appraisal of environmental cues was hypothesized to develop automatically or unconsciously through repetitive commitment of this unlawful act. Nevertheless, ease of access and egress and concealment of buildings were among the most important layout cues observed and taken into account by burglars (See Table 9).

Table 9

Measures of surveillability according to Nee and Meenaghan, tabulated by the author.

Surveillability	Description of measures
Attractiveness	(1) Degree of cover (2) Access and gateway routes

Macdonald and Gifford (1989), Shaw and Gifford (1994) and Ham-Rowbottom, Gifford and Shaw (1999) studied burglars, residents and police officers perception of vulnerability of single-family dwellings to burglary victimization, and compared their views to each another. Fifty pictures of single-family dwellings were shown to 44 convicted burglars (Macdonald & Gifford, 1989), 50 neighborhood residents (K. T. Shaw & Gifford, 1994), and 41 police officers (Ham-Rowbottom et al., 1999). Participants were interviewed and rated colorful photographs of dwellings from 1-7; 1 representing most vulnerable and 7 signifying least vulnerable dwellings on individual and combined principles of occupants surveillability, road surveillability, actual barriers, symbolic barriers, traces of occupancy and market value (See Table 10). Road surveillability was measured through the number of visible and obstructed windows from road, visibility of front door from road, visibility of building and yard from road, visibility to neighboring windows and buildings, and distance from road. Occupant's surveillability was measured through number of unobstructed windows and traces of occupancy.

The results revealed that in burglars' eyes vulnerability of single-family dwellings increases with lower degrees of road surveillability and market value when the influence of other variables are par-tailed[9] (Macdonald & Gifford, 1989; K. T. Shaw & Gifford, 1994). For residents and police officers, fewer actual barriers, fewer traces of occupancy and lower degrees of road surveillability increases burglary victimization risk when the effect of other variables are par-tailed (Ham-Rowbottom et al., 1999; K. T. Shaw & Gifford, 1994).

In sum, road surveillability was shown to be the most important predictor for burglary victimization in burglars', residents' and officers' judgments. In addition, the results of these three studies revealed that residents' and police officers' view of vulnerability risk of dwellings to burglary victimization are more correlated together than views of residents and burglars and officers and burglars. This can be explained through the fact that burglars are the only group who are involved in the act of burglary as a profession and thereby their appraisal of environmental cues may be different from others (Ham-Rowbottom et al., 1999; Macdonald & Gifford, 1989; K. T. Shaw & Gifford, 1994).

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[9] Partial correlation measures the relationship between two variables while holding a third variable constant for the two variables.

Table 10

Individual cue frequencies for the 50 houses in the study. From "Residents' and Burglars' Assessment of Burglary Risk from Defensible Space Cues," by K. T. Shaw and R. Gifford, 1994, *Journal of Environmental Psychology*, *14*, p. 194, Copyright (1994) by Elsevier. Reprinted with permission.

Individual cue frequencies for the 50 houses in the study

Cues	yes/no/missing*	Cues	yes/no/missing*
Actual barriers		no. of cars in driveway or garage	
actual barrier (e.g. fence)		0: 35	
between the property and road	17/33/0	1: 12	
gate present	11/39/0	2: 3	
gate open	10/1/39	no. of cars on street	
garage or carport present	26/24/0	0: 43	
garage or carport doors open	16/10/24	1: 7	
degree of enclosure of yard		smoke visible from chimney	5/45/0
none: 9		Road surveillability	
sides only: 20		no. of windows clearly visible from road	
completely enclosed: 21		0: 4	
back yard separated from		1: 6	
front by actual barriers	21/23/6	2: 14	
sliding glass doors	31/12/7	3: 13	
front door some glass	40/3/7	4: 7	
solid front door	8/34/8	5: 3	
screen door	26/14/10	6: 0	
glass panel beside door	23/18/9	7: 0	
glass panel is transparent or opaque		8: 2	
transparent: 8		missing: 1	
opaque: 9		no. of windows covered by shrubs etc	
missing: 33		so not clearly visible from road	
Symbolic barriers		0: 26	
street edge undefined,		1: 14	
no curb or sidewalk	25/19/6	2: 8	
ditch	35/9/6	3: 0	
sidewalk	33/11/6	4: 0	
open access to site	17/33/0	5: 0	
symbolic barrier		6: 1	
between road and yard	30/20/0	7: 0	
symbolic barrier		8: 0	
between yard and house	29/21/0	missing: 1	
symbolic barrier between		front door visible from road	37/13/0
yard and neighbors	13/34/3	at least 3/4 of house visible from road	26/24/0
home is higher than the road	8/42/0	at least 3/4 of yard visible from road	24/26/0
more than 4 steps to front door	7/43/0	neighbor's house visible	29/21/0
trees or shrubs		neighbor's windows visible	16/34/0
(more than four) in front yard	38/12/0	distance from road is less than 20 feet	18/32/0
landscaping	7/43/0	Occupant's surveillability	
weedy yard, lawn unmowed	8/42/0	noise created on approach to house	7/43/0
junk in yard		no. of windows unblocked for occupant	
(e.g. lumber, broken toys)	2/48/0	0: 16	
trash in yard or on boulevard	4/46/0	1: 11	
shutters, balcony etc.	26/24/0	2: 13	
more than three personalizations,		3: 5	
planters, or lawn ornaments	11/39/0	4: 2	
home, roof or		5: 1	
fence needs repair	47/3/0	6: 1	
house no. on property twice	2/48/0	7: 1	
house no. on road edge	11/39/0	8: 1	
beware of dog sign	48/2/0	Miscellaneous	
neighbourhood watch sign	3/47/0	no. of storeys	
block parent sign	2/48/0	1: 23	
Traces of occupancy		2: 27	
mail, flyers uncollected	4/46/0	flower beds	31/16/3
lights on inappropriately	5/45/0	shaped, trimmed shrubs	21/28/1
sign of interrupted activity	45/5/0	leaves raked	12/32/6

* Missing = missing data.

2.4.4 Residents perspective on natural surveillance and burglaries

Using census data, police recorded incidents and victimization survey across 100 census tracts in Seattle, Bellair (2000) investigated the reciprocal relationship between street crime and natural surveillance. Natural surveillance was measured through surveys inquiring whether inhabitants watch each other's properties when one is out of town (See Table 11). Findings revealed a negative reciprocal relationship between natural surveillance and robbery, but no relationship between natural surveillance and burglary rates. Nevertheless, burglary positively influenced natural surveillance after robbery/strangers assault rates were controlled, meaning that burglary occurrence may encourage residents to become more engaged in surveying activities.

Table 11

Variable names, variable descriptions, and descriptive statistics. From "Informal Surveillance and Street Crime: A Complex Relationship," by P. E. Bellair, *Criminology*, *38(1)*, p. 148, copyright (2000) by Criminology. Reprinted with permission.

Table 1. Variable names, variable descriptions, and descriptive statistics (*N*=100)

Endogenous Variables	Variable Description	Mn	S.D.
Burglary[a,b]	Principle components factor scale combining the official and victim survey burglary measures (alpha = .74)	.00	1.00
Robbery/Stranger Assault[a,b]	Principle components factor scale combining the official and victim survey robbery/ stranger assault measures (alpha = .81)	.00	1.00
Informal Surveillance[b]	Principle components factor scale combining the % that watch their neighbor's property when the neighbor is out of town (mn = 71.36, s.d. = 17.89), and the % of respondents whose neighbor watches the respondent's property when the respondent is out of town (mn = 77.22, s.d. = 15.02)(alpha = .96)	.00	1.00
Exogenous Variables			
Concentrated Disadvantage[c]	% below poverty line (mn = 12.73, s.d. = 10.02), % not in labor force (mn = 32.07, s.d. = 9.90), % female-headed households (mn = 20.24, s.d. = 9.76), and % African American (mn = 10.43, s.d. = 15.50)(alpha = .80)	.00	1.00
Residential Stability[c]	% whom have lived in the same household 5 or more years	44.29	11.92
Downtown	Dummy variable coded 1 if neighborhood is located in the downtown area, and 0 if it is not	.04	.20
Unsupervised Teens[b]	% that report teenagers hanging out on the street is a problem within 3 blocks of their home	27.62	15.37
Neighboring[b]	Principle components factor scale combining the % that borrow tools or small food items from neighbors (mn = 50.94, s.d. = 12.06), % that have lunch or dinner with neighbors (mn = 47.69, s.d. = 11.55), % that have helped their neighbor with a problem (mn = 73.08, s.d. = 8.60)(alpha = .81)	.00	1.00

Data Source: [a] Seattle Police Department, Crimes known to the police (1989–1991).
Data Source: [b] Seattle Victimization Survey (1990).
Data Source: [c] Census of Population and Housing (1990).

In a study to investigate potential house buyers' perceptions toward natural surveillance and its importance in deterring property crime, a face-to-face questionnaire was designed and taken by 208 house buyers in a property fair held in year 2008 in Sungai Petani, Malaysia. The results of the survey revealed that 88 percent of the respondents would take into account the degree that a dwelling surveys its immediate environment. 12 percent were neutral regarding the role that natural surveillance might play in preventing crime (Ismail, Shafiei, Said, & Omran, 2011).

2.4.5 Syntactical measures of space and burglaries

Using data for 11,000 detached houses in Australia with relatively similar socio-economic conditions, Hillier (2004) studied the relationship between spatial design and burglary risk. Some spatial factors like constitutedness and seclusion of buildings was taken into consideration (See Table 12). Constitutedness was quantified through taking into consideration the extent to which entrances of dwellings on both side of the street face each other. Employing logistic regression analysis, the results revealed that burglary risk increases by any secondary exposure, also that risk decreases when entrances of dwellings on both side of streets face each other.

Table 12

Measures of surveillability according to Hillier, tabulated by the author.

Surveillability	Description of measures
Natural surveillance	(1) Constitutedness (2) Secondary exposure (i.e. a corner lot, an empty, an adjacent open space, etc.)

Using police recorded crime data for two Dutch towns of Alkmaar and Gouda, Van Nes and Lopez (2010) employed correlations and risk band analysis to examine the relationship between macro and micro spatial characteristics of crime sites and geographic distribution of residential burglaries and car theft. Natural surveillance was calculated through the degree of constitutedness and intervisibility between buildings and streets (See Figure 5). A streets is considered constituted if at least one building has direct access to that segment otherwise it is regarded as unconstituted. The degree of intervisibility was calculated by dividing the number of visible doors, windows and parking lots to each opening divided by the total number of doors, windows and parking lots on that segment. Inverse relationships were found between the degrees of constitutedness and intervisibility and burglary incidents.

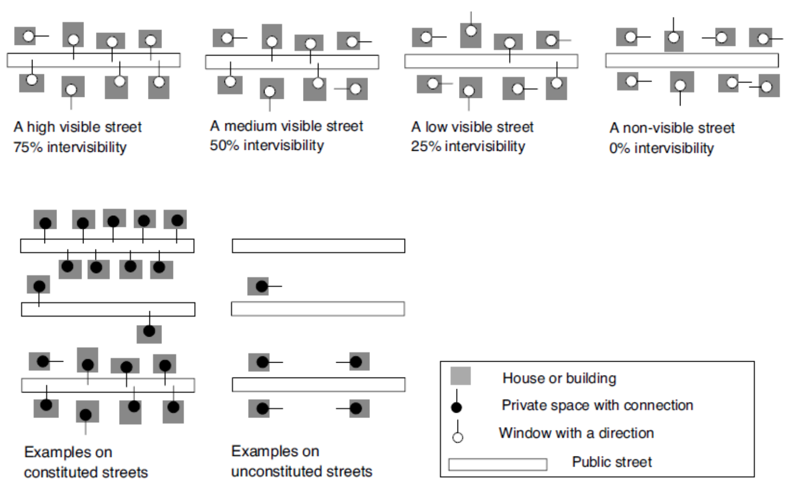

Figure 2: Diagrams showing various degrees of inter-visibility and the constitutedness - unconstitutedness relationship between buildings and streets

Figure 5. Diagrams showing various degrees of inter-visibility and the constitutedness-unconstitutedness relationship between buildings and streets. From “Macro and micro scale spatial variables and the distribution of residential burglaries and theft from cars: An investigation of space and crime in the Dutch cities of Alkmaar and Gouda,” by A. van Nes and M. López, *The Journal of Space Syntax, 1(2)*, p. 304, copyright (2010) by The Journal of Space Syntax and Akkelies van Nes. Reprinted with permission.

2.4.6 Landscape features and burglaries

Kuo and Sullivan (2001) were among the first to quantify the relationship between vegetation and crime. Utilizing Chicago Police Department year-end uniform reports, aerial photographs, site analysis and Chicago housing authority data, Kuo and Sullivan investigated the relationship between vegetation and property and violent crimes over a two-year period for 98 apartment buildings.. Results revealed significant negative relationships between all types of crimes and vegetation.

Troy, Grove and O'Neil-Dunne (2012) studies the relationship between density of vegetation canopy and density of combined burglary, robbery, shooting and theft crimes in Baltimore, MD. Data for this study were obtained from high resolution color infrared imagery, LiDAR data, spotcrime data, and census data. The results of ordinary least squares regression and spatially adjusted regression revealed a significant inverse relationship between density of vegetation canopy (i.e. street vegetation, yard vegetation and combinations of both) and index of crime for most block groups even after controlling for some socio-economic variables. However, when industrial and residential block groups blended into one another, the relationship between vegetation and crime densities became significant and direct.

Wolfe and Mennis (2012) further investigated the relationship between vegetation and rates of assaults, burglaries, robberies and thefts at the Census tract level in Pennsylvania, PA. NASA's Landsat 7 imagery, the CrimeBase dataset and census data constituted primary source data for this study. Employing correlation and ordinary least squares regression, statistically significant direct relationships were found between vegetation density and rates of assaults, burglaries and robberies. This positive relationship held after controlling for Census tracts measures of poverty, educational attainment and population density. No relationship was found between abundance of vegetation and rates of theft.

Donovan and Prestemon (2012) investigated the relationship between greenery and burglary of single-family houses (in addition to some other types of crimes) for a three-year period in Portland, Oregon. Portland police bureau crime data, Multnomah County Assessors data, aerial photographs and site surveys constituted the primary source of data for this study. Results of probit model revealed that smaller trees are positively associated with incident of burglaries as smaller trees may obstruct views, but larger trees are inversely associated with burglary incidents.

2.4.7 Summary

The review of literature on natural surveillance revealed that this principle of CPTED has been analyzed in the following ways:

- Subjectively grounded on assumptions or retrieved researchers' judgments of whether or not a dwelling can be seen from other dwellings (See headings 2.4.1 and 2.4.2).
- Subjectively grounded on interviews inquiring and comparing burglars', officers' and residents' views on vulnerability of dwellings to burglary (See heading 2.4.3).
- Subjectively based upon surveys inquiring whether or not residents monitor activities in their residential quarters (See heading 2.4.4).

- Objectively in two dimensions without taking into consideration the height and surveillance characteristics of surrounding features such as buildings and vegetation (See headings 2.4.5 and 2.4.6).

Much research is based on researchers' judgments on natural surveillance characteristics of dwelling. In these observational studies, surveillability to and from houses or building openings are mainly evaluated in situ. Firstly, assuming that researchers stayed in public land for their assessments, their judgments cannot necessarily represent whether building openings were visible to and from other neighboring building openings and roads. Secondly, having certain architectural and landscape features (i.e. porch, verandah, fencing, vegetation, etc.) does accurately convey whether views to and from buildings were enhanced or obstructed by these features (See headings 2.4.1 and 2.4.2).

Some other research is grounded on interviews conducted with burglars, officers and residents on vulnerability of dwellings to burglary risk. In these studies, pictures of burglarized and non-burglarized dwellings were shown to participants, and their views toward vulnerability of dwellings to burglary were inquired. However, firstly, the sense of place cannot be fully conveyed through photographs and secondly, location of buildings to adjacent land uses was overlooked (See heading 2.4.3).

In addition, inquiring residents on whether they value natural surveillance or monitor their neighbors' properties does not depict information on whether the feeling of safety was perceived or visual perception really took place. It should be kept in my mind that neighbors may not be able to observe all openings to adjacent premises (See heading 2.4.4).

A few other sources objectively analyzed natural surveillance based on 2-dimensional syntactical measures of space or 2-dimensional density of vegetation. Judgments on the degree of surveillability of building openings based on 2-dimensional maps may be restricted. For instance, vegetation has been considered as an important factor in obstructing views; however, relating vegetation densities to crime rates without taking into consideration the approximate or exact height of trees does not necessarily capture whether views to and from building openings are obstructed (See headings 2.4.5 and 2.4.6).

Thus, instead of making subjective judgments on the degree of natural surveillance of building openings or buildings through observation studies (in situ), interviews (from pictures) or questioners (by inquiring questions), I seek to expand the objective 2-dimensional approach to the third dimension. Thus, by taking into consideration height, size and precise location of architectural and landscape features on the surface of the earth, (1) natural surveillance was quantified in 3-dimentions; (2) the degree of surveillability of building openings and buildings to their adjacent building openings, buildings, road and pedestrian network was measured and quantified, and (3) restrictions and precise measurements was applied to the length of sightlines according to the range human eye can effectively observe its surrounding. The following sections show how natural surveillance can be quantified in the era of digital spatial information revolution.

2.5 The Era of Digital Spatial Information Revolution

We are in the era of digital spatial information revolution (LeGates et al., 2009) grounded on geospatial data and technologies able to support scientific studies of cities, emerging behaviors of people and the relation between the two. This wave has provided innovative opportunities for designers and planners to enhance their spatial thinking skills and to study cities and their complexities scientifically. The era of digital spatial information revolution has implications for classical theories of place-based crime prevention, for instance spatial configurations (i.e. natural surveillance, etc.) can be quantified and field contingent behavior (i.e. criminal activities, etc.) can be more rigorously explored and studied.

2.5.1 Theories in the era of digital spatial information revolution

Theories that dominate in the era of digital spatial information revolution (LeGates et al., 2009) include but are not limited to virtual reality models, micro-simulation models, fractal cities, space syntax and GeoDesign. The following sections are devoted to elaborate on theories that have been utilized or can be employed for space-crime studies.

2.5.1.1 Micro-simulation models

Micro-simulation models (cellular automata models and agent based models) are developed upon statistical physics models, which are themselves inspired by laws of physical and social sciences (Schadschneider, 2002). Micro-simulation models seek to investigate the emerging behavior of individuals in large scale urban settings. The basic tenet of micro-simulation models is that complex networks emerge from bottom-up, and thereby cities and their complexities should be studied with a bottom-up perspective (Blue & Adler, 2001; Crooks, Castle, & Batty, 2008).

Analyzing complex systems through the use of micro-simulation models initiates with modeling agents having different characteristics. Agents, be they potential criminals or benevolent others, are overlaid over a uniform grid placed on urban layouts. Each cell in the grid is assigned a value (or several values), which rules the state of each cell relative to its neighbors. Agents are released to the grid to reach predefined goals with the capacity to interact independently while taking into account environmental obstacles and behavior of other agents (Clifton, Davies, Allen, & Radford, 2004).

2.5.1.2 Space syntax

Space syntax, grounded on mathematical graph theory, network analysis and topological notions of spatial perception, is a set of methodologies and techniques for socio-spatial analysis. Space syntax takes space as an independent variable and tests impacts of spatial configurations on societal and anthropological outcomes (Hillier, 2007; Hillier & Hanson, 1984). According to Ratti (2005), space syntax is a representation of aggregative models of spatial analysis since correlation is made between two variables; urban indicators (i.e. measures of connectivity, integration, etc.) as independent variables and aggregate social factors (i.e. flow of people, crime, etc.) as dependent variables. The notion of space syntax comes from linguistics conveying that even though generative algorithms can produce an unlimited number of spatial configurations, a finite number of these configurations are meaningful and instinctively comprehensible to people (Hillier, 2007; Hillier & Hanson, 1984).

Space syntax has three fundamental components: (a) axial lines, (b) convex spaces and (c) isovist fields. Axial lines are used for movement studies; convex spaces for interaction studies; and isovist fields for behavioral pattern or orientation studies (Hillier, 2004; Van Nes, 2011). Syntactical measures of space (i.e. connectivity, choice, skeweness, roughness, etc.) are later assigned on these representations and are computed taking into account the relationship between each element and all other elements in the layout. This well-known technique of socio-spatial analysis has been criticized mainly because of its reliance on axial maps (Ratti, 2004a, 2004b; Steadman, 2004).

Space syntax has been widely applied to investigate the relationship between syntactical properties of space and patterns of crime (Hillier, 2004, 2007; Shu, 2000; Van Nes & López, 2010). According to Hillier (2004), there are three main reasons to employ space syntax for crime patterns studies; firstly, natural policing or natural surveillance is affected by vehicular and pedestrian movement; therefore, a methodology representing movement potentials at the level of street segment is desirable. Secondly, this method of urban analysis does not exclude social structures from spatial configurations and provide opportunities for studying micro and macro spatial variables with equal rigor. Thirdly, incorporating space syntax, numerical values can be assigned to macro and micro spatial variables, making the quantified space appropriate for statistical analysis along with other numerical social, economic and demographic characteristics.

Space syntax theory has been less acknowledged by design and planning researchers and academics in the United States. Several social and technical obstacles exist for the adoption and employment of space syntax in the United States (Raford, 2010). Technical barriers were categorized as; (a) reluctance to the acceptance of axial lines as a representation for spatial configurations; (b) dependency on a complex software, Depthmap, developed by the space syntax laboratory; (c) difficulties in fully grasping the mathematical terms of space syntax mainly grounded on graph theory; and (d) analytical rather than prescriptive nature of this approach which demands additional data interpretation and analysis. Regarding social challenges, preference to other widely employed connectivity measures and epistemological distinctions between space syntax and design education and profession in United States can be pointed out (Raford, 2010).

2.5.1.3 Geographic information systems (GIS) and GeoDesign

Geospatial technologies are comprised of geographic information systems (GIS) in addition to remote sensing, mobile computing, computer aided design and visualization techniques among other techniques (LeGates et al., 2009, p. 764). Geospatial technologies are techniques for collecting and managing geographic data. ESRI ArcGIS is a computerized system which enables researchers and practitioners to visualize, query, study and infer relationships, patterns and trends that underlie geospatial variables (Esri, 2014b). Geographic information systems have long being enhancing environmental understanding, protection and decision making and have been widely used by different academicians and professionals for operational (i.e. transportation, defense, etc.), social (i.e. health and healthcare, etc.) and environmental (i.e. environmental monitoring and assessment, etc.) applications (Longley, Goodchild, Maguire, & Rhind, 2005).

GeoDesign is a concept which brings GIS into the process of design. The concept of GeoDesign is grounded on fields such as architecture, landscape architecture, environmental studies, geography, planning and regenerative and integrative studies. GeoDesign thereby takes an interdisciplinary approach to rigorously solve the wicked[10] problems of design. The framework for GeoDesign is comprised of representation models, process models, evaluation models, change models, impact models and decision models (See *Figure 6*). This framework fully leverages geospatial data and technologies to make iteration through multiple design solutions, to shorten the design process and to minimize undesirable impacts of design and planning decisions (Esri, 2010; Steinitz, 2012).

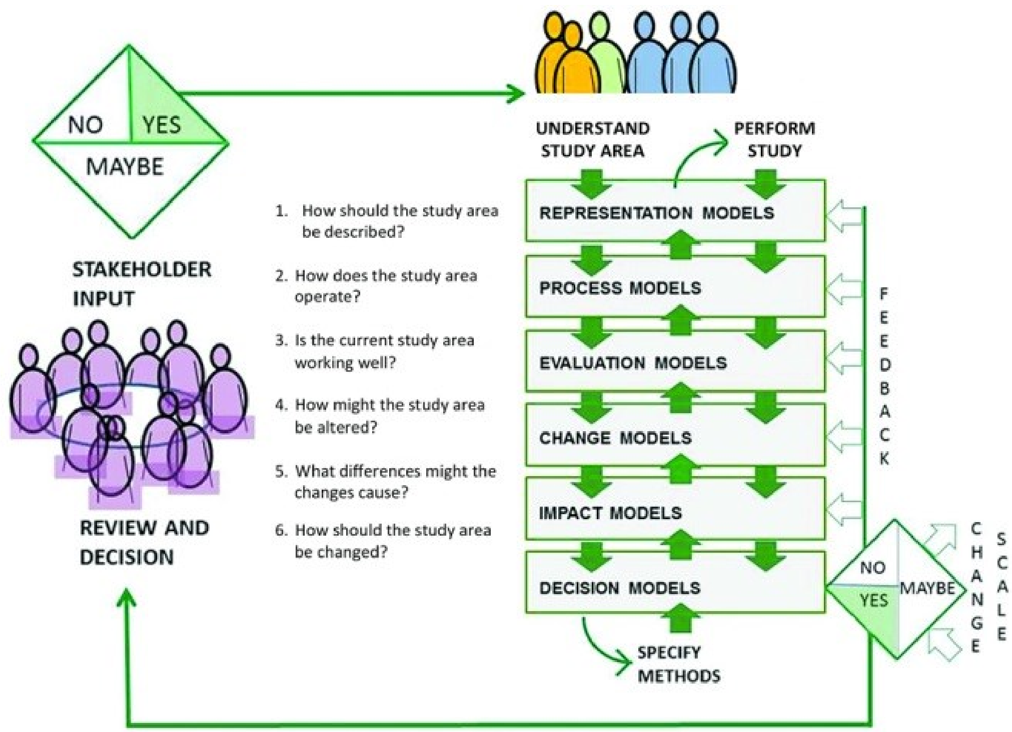

Figure 6. The stakeholders, the geodesign team, and the framework for geodesign. From *A Framework for Geodesign: Changing Geography by Design* (p. 25), by C. Steinitz, 2012, Redlands, CA: Esri Press. Copyright (2012) by C. Steinitz. Reprinted with permission.

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[10] Design problems are wicked problems (Buchanan, 1992). Wicked problems have no definitive formulation or stopping rule; are unique; and influenced by designers' worldview. In addition, solutions provided for wicked problems are one-shot operations because designers cannot resort to and learn from trial and errors methods.

2.5.2 Visibility studies

Disciplines ranging from perception psychology to urban ethnography and from urban ethology[11] to urban geography have taken into account visibility parameters for human-environment studies. Lynch (1964, 1976) among others, took the first attempts to analyze visibility and grounded his analysis on mapping and qualitative techniques. Later, 2-dimensional, 2.5-dimensional and 3-dimensional computerized techniques were introduced for visibility analysis taking into consideration horizontal, vertical or both aspects of visual perception.

Various disciplines developed notions and tools based upon their needs and the technology of the time. The field of architecture introduced the notion of isovist (Benedikt, 1979; Davis & Benedikt, 1979; Tandy, 1967), the field of geoscience introduced viewshed and the line of sight analysis (Ervin & Steinitz, 2003; Esri, 2014a; Fisher, 1996) and the Naval Research Laboratory developed a software, called Sniper RT, which checks line-of-sight from any point on a map (Peck, 2013). The following sections discuss innovative open-source techniques developed for analysis and quantification of visibility in 2π radians or 360 degrees.

2.5.2.1 Isovist

The term isovist was first coined by Tandy (1967). Later, Benedikt (1979) expanded this notion and undertook initial attempts to introduce analytical measurements for isovist and isovist fields (Weitkamp, 2011). Benedikt (1979) defined an isovist as "the set of all points visible from a given vantage point in space and with respect to an environment" (p. 47). Thus, the shape, size

[11] Urban ethology is studying the behavior of human beings and animals in the environment.

and measures of isovist alter with observers' position and change of position in space. Furthermore, characteristics of an isovist form point x in space (V_x) are not only dependent upon the vantage point but also on the larger environment.

Assuming that isovists have boundaries, the border of an isovist can be broken down into: real surfaces (S_x), occluding radial surfaces (R_x) and region-boundary surfaces (∂D_x) (Benedikt, 1979, p. 50) (See *Figure 7*). Based upon these units, Benedikt and colleagues (1979) developed some two-dimensional analytical measures for isovist which are briefly discussed in the following;

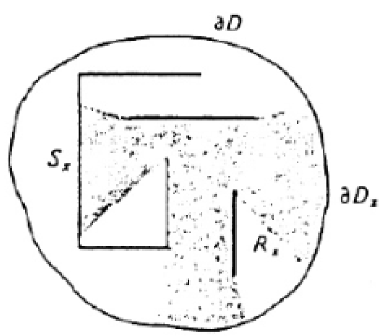

Figure 7. The boundary, ∂Vx, of an isovist, decomposed into S_x, R_x, ∂D_x. From "To Take Hold of Space: Isovist and Isovist Fields," by M. L. Benedikt, 1979, *Environment and Planning B: Planning and Design*, *6*, p. 50, Copyright (1979) by Pion Ltd, London (www.pion.co.uk and www.envplan.com). Reprinted with permission.

1. The *area* of an isovist (A_x) conveys how much space can be viewed from a vantage point and from how much space the vantage point can be observed.
2. The real-surface *perimeter* of an isovist (P_x) implies how much of the (real) surface of an environment can be seen from a vantage point.
3. The *occlusivity* of an isovist (Q_x) computes the depth of the occluding radial boundary and measures the depth that environmental affordances cover each other.

4. The *variance* of radials ($M_{2,x}$) depicts the dispersion of perimeter corresponding to the vantage point.
5. The *skeweness* of radials ($M_{3,x}$) measures the asymmetry of variance corresponding to the vantage point.
6. The *circularity* of an isovist (N_x) is another way of computing compactness or complexity and is the ratio of perimeter to area.

Later, Benedikt (1979) proposed that understanding spatial configurations may demand a series of isovists and herein the notion of isovist was expanded to isovist fields. Isovist fields are presented through counter lines, with dense counter lines conveying rapid information change in space and sparse counters presenting fewer change in spatial information (Benedikt, 1979; Davis & Benedikt, 1979).

Davis and Benedikt (1979) hypothesized that isovist measures do not only open the avenue for strategic design of minimal specifications of the building design (i.e. walls, building openings, etc.) but also shed light on studies of desired experiences of human beings in space (i.e. privacy, safety, etc.). Thus, different environments may possess unique different isovists which could represent some unique cognitive, perceptual or experiential factors of spatial configurations. For instance, measures of area (A_x) and occlusivity (Q_x) were hypothesized to predict occurrence of assaults, burglaries and vandalism as offenders want to be inconspicuous and safe from detection. Therefore, places of local minima in area with positive value in occlusivity were proposed to be spots of crime.

Davis and Benedikt (1979) called for further research to investigate whether their propositions apply. Some applications of their concept are reviewed in the following paragraphs; however, after more than three decades, to what extent isovist, isovist measures and isovist fields may relate to human perception and behavior is still an open avenue for further research (Benedikt, 1979; Ratti, 2005; Turner, Doxa, O'Sullivan, & Penn, 2001).

Concentrating on isovist measures of distance, area, perimeter, compactness and convexity, Batty (2001) computed isovist fields for a geometric shape, a gallery, a street and a town center. Through adoption of a software called StarLogo from the MIT media lab, isovists are computed through releasing agents to space, and counting the number of steps agents walked in a given direction before colliding to a building façade or a wall. Batty hypothesized that architecture and urban morphology cannot be fully measured by geometries per se, instead isovists emerging from geometries may better represent morphological characteristics of architectural and urban layouts.

In a study to investigate the extent to which isovist measures may predict enclosure or spaciousness impression, Stamps III (2005) analyzed twenty five different variables of isovists for 15,521 environments and concluded that horizontal size and concavity, variations in distance to boundary, to elongation, to nearest distance, and to boundary predictability are the most credible measures of isovist. Visible area of an isovist provides the chance of observing potential criminals. Concavity conveys that there could be spaces where potential offenders can hide. Variations in distance to boundary imply a direct relation between unbroken sightlines and protection. Elongations represent restrictions in lateral movement. The nearest distance is the radial that most people respond to, and boundary predictability implies that potential enemies can be detected easier.

Shach-Pinsly (2010) analyzed the degree of visual openness and visual exposure for a typical building configuration in addition to three alternatives to the existing urban fabric in Haifa, Israel. Visual openness is referred to the view from one's private space and was measured through computing isovist fields for the inner open public space and the outer open space surrounding the setting. Visual exposure is related to privacy and may be disturbed by visual intrusion into individual's private space. The degree of visual exposure was quantified through measuring the distance between each window and all other windows in the building layout. Visual exposure was analyzed at each floor and in three dimensions between buildings through generating sightlines from every window to all other visible windows. Shach-Pinsly demonstrated that analyzing the degree of visual openness and visual exposure of building layouts during the design process can help determine the impact of architectural designs on residents' quality of life.

2.5.2.2 Visibility graph analysis

Drawing upon graph-based representations of space, Turner (2003) and Turner et al. (2001) extended the notion of isovist to visibility graph analysis in order to study (a) how spatial configurations influence social functions in architectural and urban space and (b) how common experience of space can be captured. A set of locations were selected for generating isovists (graph vertices) then visibility and permeability relations between vertices were measured (graph edges). Introducing visibility graph analysis, two further measures of graph theory, the clustering coefficient and the mean shortest path length were computed. The clustering coefficient provides "a measure of the proportion of intervisible space within the visibility neighbors of a point" (Turner et al., 2001, p. 110) and conveys how much of spatial information will be retained or lost as people move away from vantage points. The mean shortest path length for a given vertex is "the average of the shortest path lengths from that vertex to every other vertex in the system" (Turner et al., 2001, p. 114) and represents how accessible various locations are in respect to each another. Turner hypothesized that the process of inhabitation (be in walking along a footpath or enjoying a painting) encompass interactions; therefore, visual dynamics of urban morphology represent a dialogue between "the phenomenological account of architecture" and "the logical account of phenomena within architecture" (Turner, 2003, p. 674). As a result, instead of measuring visibility in vacuum, the visual process of inhabitation should be assessed and studied.

Desyllas, Connoly and Hebbert (2003) developed a design-evaluation tool for modeling natural surveillance in public spaces using visibility graph analysis. Visibility graph analysis (VGA) involves overlaying a uniform grid over public spaces and obtaining visibility relationships of each cell in the grid to every other cell. VGA was employed to compute isovists from entrances of all buildings in a traditional street grid area with terraced buildings covering an area of 48,300 m^2 (of which 69 percent was built) and from a contemporary university campus with detached buildings encompassing an area of 45,453 m^2 (of which 29 percent was built). The model was adjustable in regard to three parameters: myopic distance[12], grid density of VGA, and

[12] "Myopic distance, or distance at which sight is no longer considered effective" (Desyllas et al., 2003, p. 647).

building entrance characteristics. The overlaid grid can be computed at any density; however, the denser the grid, the higher the computation time but the finer the resolution. Characteristics of building entrances are contingent upon the survey data details and can range from assigning similar symbologies to doors to differentiating entry points according to their widths and number of doorsteps. This study revealed lower amounts of unsurveyed space and greater intensity of natural surveillance for the traditional street networks compared to a modern university campus.

2.5.2.3 Viewshed

Viewshed and Isovist are two mutual terms, the former mostly used by architects and the later by geoscientists. Isovist and viewshed are both perception-based models of visibility analysis as visual perception of perceivers from the surrounding environment is returned rather than pure depiction of objects (Weitkamp, 2011). Viewshed can be represented by "defining one location as the viewing point and then calculating the line-of-sight to every other point within the area of interest" (Fisher, 1996, p. 1297). Viewshed analysis can be performed in the ArcGIS platform, and surface locations on a raster observable to one or more observer features may be determined (Esri, 2014a).

The viewshed algorithm is centered on line arrays connecting target and observers. In order to determine whether target locations are visible or nonvisible, the elevation difference of intermediate pixels between target and observer cells is taken into account. Sightlines will be generated between observer and target cells and targets are considered visible if the land surface rises above the sightlines and nonvisible if the land surface falls below these lines. Viewshed analysis is a laborious task taking into account the number of the cells for which visibility is to be computed (See *Figure 8*).

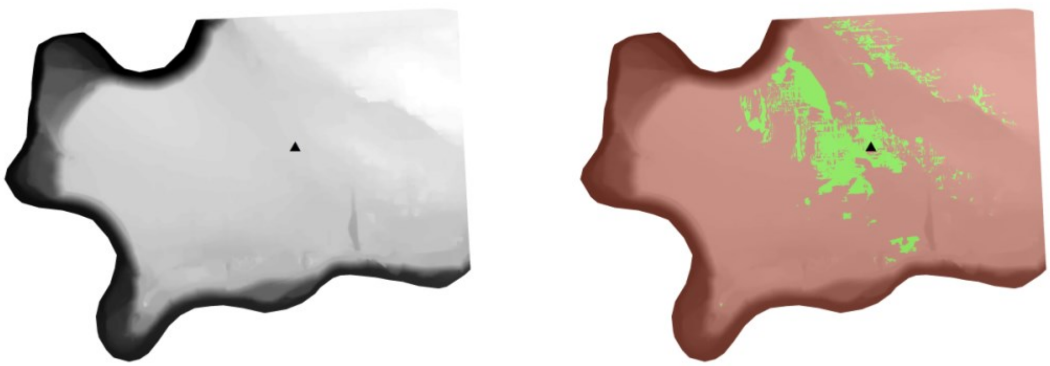

Figure 8. Viewshed analysis in ArcGIS. Left: Input DEM with an observer point. Right: Output viewshed (Source: Author).

Viewsheds are considered as the first derivative of the terrain surface, and measures of viewshed may be considered as the second derivatives of that surface. Ervin & Steinitz (2003) introduced some measures for viewsheds, but provided a definition for area of viewsheds. I further studied these measures and developed definitions for them. Measures and their definitions are presented below:

1. The area of a viewshed depicts the area that can be viewed from the viewshed and locations that can view the observer point (Ervin & Steinitz, 2003, p. 760).
2. The longest reach of a viewshed conveys the longest distance from the observer location to the farthest visible surface.
3. The roughness measure of viewshed's perimeter is the extent of the surface of the environment seen from the observer point.
4. The aspect ratio of viewshed's major and minor axes implies a ratio between viewshed's longest and shortest radial.

5. The presence and number of islands in a viewshed convey the existence and number of invisible polygons in the viewshed boundary.

Employing viewshed analysis, it can be measured and quantified from how many observer points a target point can be viewed, and how many observer points are visible to a particular target point. Some limitations for viewshed analysis apply. Firstly, viewshed analysis is based on 2.5 dimensional data since each location on the earth's surface can only have one z-value. Secondly, the viewshed algorithm does not incorporate the vertical viewing angle into the analysis of visibility. Lastly, viewshed analysis is grounded on a binary query, retrieving 1 or 0 for in-sight or out-of-sight locations (Ervin & Steinitz, 2003; Fisher, 1996). Nevertheless, viewshed analysis has its own implications and can be applied to evaluate visual impacts of new developments or planning visible areas for recreation and routing purposes (Ervin & Steinitz, 2003; Fisher, 1996).

2.5.2.4 Line of sight analysis

There has always been an urge to account for the vertical dimension when human's perception of space is returned. The line of sight analysis along with other 3D analyst tools available in the ArcGIS platform, is a visibility tool that overcomes the aforementioned limitations of isovist and viewshed analysis. The line-of-sight analysis does not only take into account the Z dimension but also consideration can be made regarding the myopic distance of human beings for analysis of visibility. Sight-lines can be constructed from points as observers to points/lines/polygons as target features. Then intervisibility between the first and last vertex of all lines can be computed given their positions in 3-dimensional space, and visible and nonvisible segments of line features will be identified (See *Figure 9*).

I could not locate any study to date having employed the line of sight analysis or other visibility tools available in the ESRI ArcGIS platform to quantify natural surveillance in 3-dimentions and relate the measured intensity of natural surveillance to commission of crimes or disorder (i.e. burglary commissions). I intend to explore this relationship by first mapping and enumerating and then comparing to burglary commissions the degree or intensity of natural surveillance in a residential neighborhood. For analysis of visibility, information on myopic distance or eyewitness identification distance is also required. Therefore, the following section is devoted to review the literature on eyewitness identification distance.

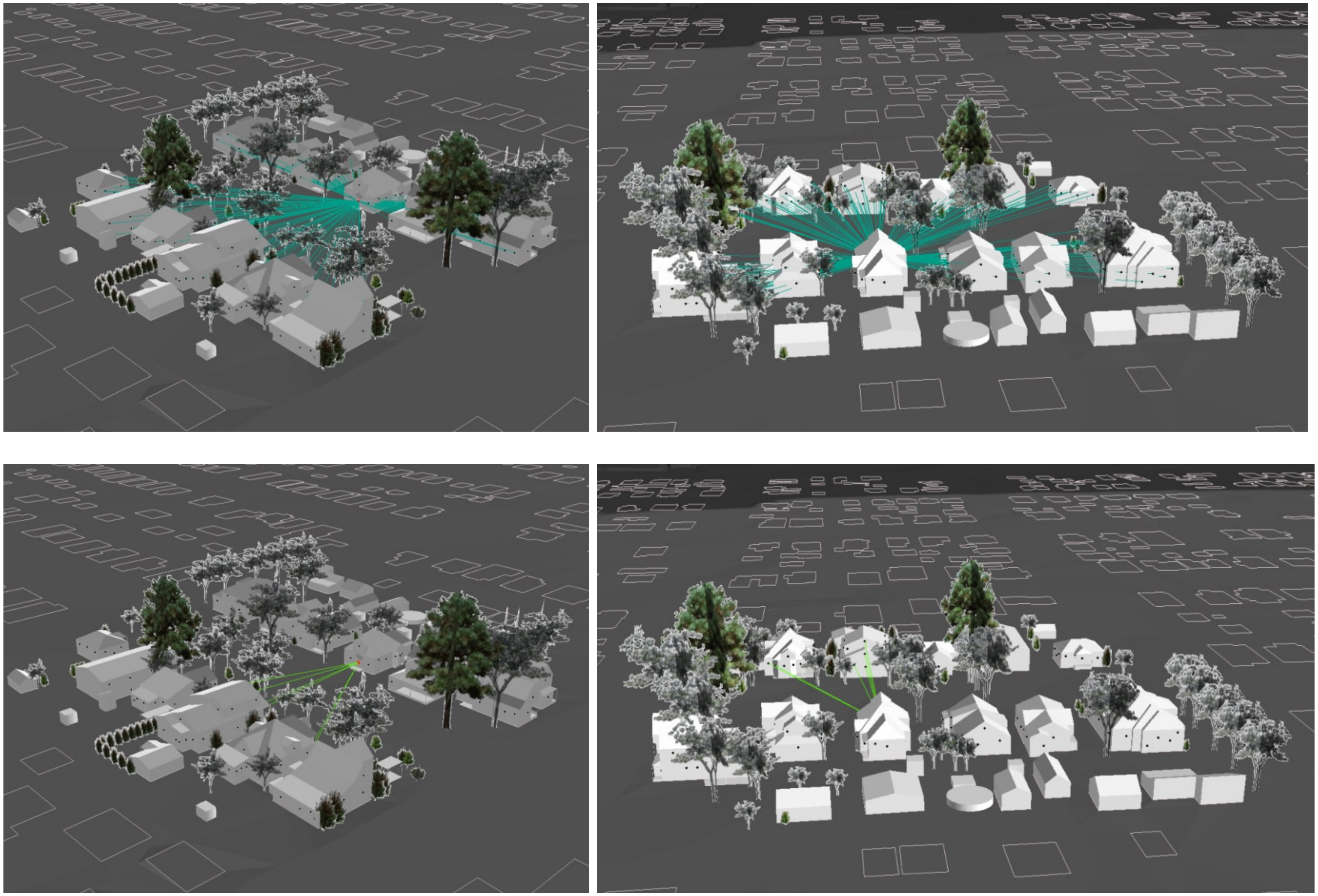

Figure 9. Line of sight analysis in ArcGIS. Top (Left and Right): Construct sight line tool was used to generate sightlines from observer points to a target point. Bottom (Left and Right): Line of sight tool computed visibility along sightlines after obstructing sightlines by architectural and landscape features (Source: Author).

2.5.2.5 Eyewitness Identification Distance

One way to uncover the truth about crimes is from eyewitnesses. Crime witnesses can provide critical information on crime incidents and criminal identification; however, eyewitness evidence can be most reliable if all intervening variables that play a part in eyewitnessing are taken into account and investigations are based on sound protocols. Factors like age, sex, race, memory skills, visual acuity, stress and anxiety level, exposition and retention time, distance, and illumination among others may play a critical role in reliability of eyewitness evidence.

Two reports released by the National Institute of Justice (Technical Working Group for Eyewitness Evidence, 1999, 2003) explored how eyewitness evidence can be collected, preserved and enhanced. However, none of these reports discuss the importance of distance in eyewitness evidence. Nevertheless, the importance of distance in eyewitness evidence has long being acknowledged and studied (De Jong, Wagenaar, Wolters, & Verstijnen, 2005; Greene & Fraser, 2002; Lindsay, Semmler, Weber, Brewer, & Lindsay, 2008; Loftus & Harley, 2005; Maclean, Brimacombe, Allison, Dahl, & Kadlec, 2011; Wagenaar & Van Der Schrier, 1996). Lab settings and natural environments were used to study the distance at which human eye can or can no longer witness and properly interpret malicious events.

Wagenaar and Van Der Schrier (1996) showed pictures of 49 unknown individuals to 56 students at 7 distances (3 to 40 meters) and 9 illumination levels (0.3 to 3000 lux). Each picture was shown for 12 seconds, immediately followed by photo lineup in a lab environment. According to Wagenaar and Van Der Schrier, face recognition performance is negatively related to distance and directly associated with illumination. This study revealed that reliable recognitions take place in distances lower than 15 meters (49 feet) with minimum illumination level of 10 lux (urban area with bright street light during nighttime hours).

Employing Wagenaar and Van Der Schrier's (1996) approach, De Jong, Wagenaar, Wolters and Verstijnen (2005) showed pictures of famous people and their lookalikes to 65 students in order to explore whether differences in face recognition distance exist between familiar and unfamiliar faces. The authors concluded that the most reliable face recognition for both familiar and unfamiliar faces takes place at the distance of 15 meters or lower with illumination level of 10 lux or higher.

Instead of carrying out studies in lab settings, Greene and Fraser (2002) showed pictures of celebrities to 16 students in midmorning and early afternoon hours in a lawn like environment. No constraint was placed on exposure time, and subjects were allowed to look at pictures until they either recognized or failed to recognize the celebrities. Employing t-tests, it was revealed that the distance at which men and women recognize celebrity pictures is significantly different from one another. The overall mean recognition distance for men and women was 113 feet and 93 feet accordingly. Further, this study revealed that at distances exceeding 340 feet for men and 260 feet for women, no face recognition takes place. It was also indicated that very few faces are recognizable at the 200 feet distance.

Authors of the previous studies acknowledged the fact that pictures are static and do not depict people's characteristics like gait or gesture among others. In addition, it was noted that people's judgment may vary in real situations, and factors like stress, familiarity with people and exposition time influence identification abilities of witnesses (De Jong et al., 2005; Greene & Fraser, 2002).

Loftus and Harley (2005) made initial attempts to develop quantitative tools for measuring the relationship between the loss of facial details as a function of distance. Carrying out four experiments in lab environments, pictures of celebrities or simulated pictures were shown to 24 or 32 students. Images were either filtered or shrunk for recognition purposes. Loftus and Harley proposed that the most reliable face recognitions take places at the 25 feet distance. The authors further explained that there is still some value in face recognition at the 77 feet distance; however, no recognition takes place at or beyond the 110 feet distance.

De Jong et al. (2005) and Loftus and Harley (2005) considered pictures of celebrities or famous people to be a good exemplar for face identification of familiar individuals. Still, these authors postulated that we most probably recognize our family members, friends and neighbors better. However, both studies may be critiqued for the fact that when pictures of celebrities or famous people are shown to individuals, real perception might not have taken place. Instead, observers may tend to make judgments or guesses upon seeing the global facial features of shown individuals.

Taking a unique approach, Lindsay et al. (2008) recruited 1,321 individuals during daily activity hours to investigate the relationship between face recognition and distance, age, weight and height among some other factors. Participants were approached without providing explanation on the purpose of the study (face identification), but their attention was directed to targets as in real situations. After experimenting with 7 distance groups ranging between 5 and

50 meters, the results revealed that minimal error for face recognition takes place at the 15 meter (49 feet) distance; however, some value or accuracy can still be found at the 43 meter (141 feet) distance. This study didn't find statistically significant relations between height, weight and age and face recognition abilities of participants.

To the knowledge of the author, Lindsay et al. (2008) study is the only study conducted in a real world environment instead of land settings. In addition, that study can be resonates with real-world situations, in which a possible observer looking out of a window perceives a criminal or suspicious activity, and through partially or fully recognizing face, gait or gesture of the intruder makes a judgment that whether or not a break-in is taking place.[13] Therefore, the unit of analysis for my study is grounded on findings of Lindsay et al. research.

2.6 Conceptual Framework

The conceptual framework for this study has three parts (See *Figure 10*). Variables that constitute this framework are based on a review of previous literature and field observations of the study area. The first part takes into consideration architectural and landscape features for creating a 3-dimensional model of a residential neighborhood upon which 3-dimensional measures of natural surveillance are later nested. These features are comprised of surface morphology, building features, vegetation and visual barriers. Eyewitness identification distance acts as a funnel for restricting the range human eye can witness and interpret malicious events.

[13] In a study to explore how guardians distinguish between potential offenders and benevolent others and what makes individuals respond to suspicious activities in their immediate environments, 255 semi-structured interviews were conducted in 13 neighborhoods in The Hague and Qud-Ade in the Netherlands (Reynald, 2010). Five observable behavioral characteristics of potential offenders were discussed as antisocial behavior, secretive behavior, aimlessness, nervousness, and eyeing potential targets.

The second part of the framework consists of some spatial characteristics of dwellings and neighborhood layouts hypothesized to influence burglary victimization by previous research. I categorized these variables under the title of planning and zoning related features and regulations, as I believe that policy and regulations can alter or influence these characteristics. Variables are comprised of building use, placement of non-residential facilities in residential quarters, maintenance, adjacency to a vacant lot, being a corner or middle lot, availability of no-trespassing signs, property demarcation through fencing and type of street network circumscribing dwellings. Some of these variables can indirectly play a part on variations of natural surveillance intensity.

The third part constitutes of not only the address of burglarized dwellings but also burglars' point of entry. The three parts of this model shape the independent, control and dependent variables for the study of burglary commissions as influenced by the degree of natural surveillance and controlled by some other spatially important spatial characteristics of dwellings and neighborhood layouts. The uniqueness of my conceptual framework is twofold; firstly, based on cutting edge technologies in the current era, my model takes into account the vertical viewing distance along with horizontal dimensions for objectifying analysis of visibility in 3-dimentions. Secondly, I take into consideration the distance at which human eye can be effective for observing and interpreting an eye-witnessed event.

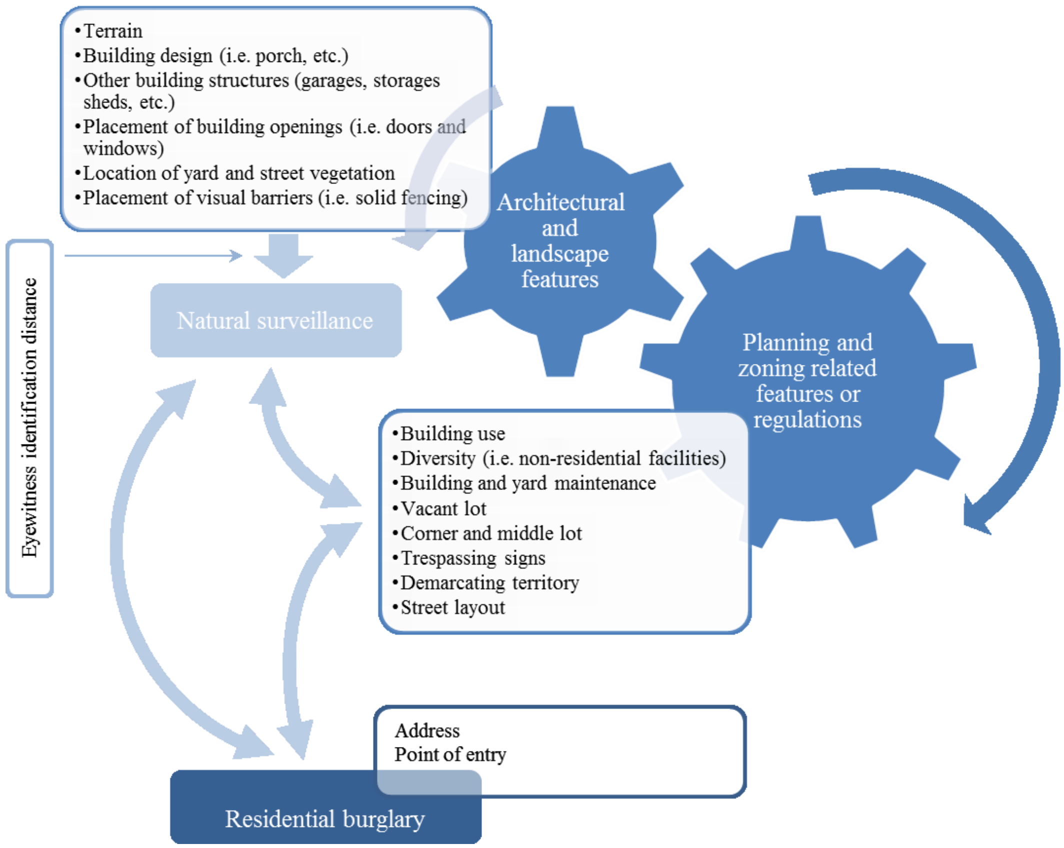

Figure 10. Conceptual framework (Source: Author).

2.7 Summary

I reviewed classical place-based crime prevention theories and identified physical design factors hypothesized to play a part in incidents of crime. I selected one of the least understood and studied principle of CPTED - natural surveillance and explored how that notion has emerged. I then studied how natural surveillance has been measured and its relationship to residential burglaries has been studied. Next, I identified a new geospatial technique for quantifying natural surveillance which overcomes the limitations of previous studies for not objectively taking into consideration the vertical viewing distance in analysis of visibility. Lastly, I proposed a new framework for studying and understanding crimes with a spatial visibility component.

3 METHODOLOGY

3.1 Introduction

This chapter concentrates on an application of georeferenced data and geospatial technologies for analyzing spatial and crime data. I first utilized georeferenced data to collect information on architectural and landscape features on the surface of the earth. I then employed geospatial technologies to create 2-dimensional and 3-dimensional models for architectural and landscape features. I next collected and georeferenced crime incident data followed by linking spatial and crime datasets. Independent, dependent and control variables for this study are presented. Lastly, I introduced a new methodology for studying and quantifying natural surveillance based on georeferenced data, geospatial technologies and eyewitness identification distance.

3.2 Research Design and Methods

The purpose of this research was first to map and enumerate, and then to compare to burglary commissions, the degree or intensity of natural surveillance in 3-dimentions in an area of Spokane, Washington. I also sought to create an enhanced model and methodology for studying other crimes such as graffiti or car theft with a natural surveillance component.

To this end, I employed an embedded mixed methods research design. In embedded research designs, qualitative/quantitative data are embedded and provide a supportive role for quantitative/qualitative data and analysis (Creswell, 2009; Creswell & Plano Clark, 2011). In my study, qualitative data were comprised of making sketches from oblique aerial imagery, field observations of architectural and landscape features, studying crime incident reports and field observation of crime sites. Quantitative data were developed from qualitative data in the ArcGIS platform, and were comprised of georeferenced spatial and crime data. Analysis of datasets and interpretations were all based on measures developed from quantitative data (See Figure 11).

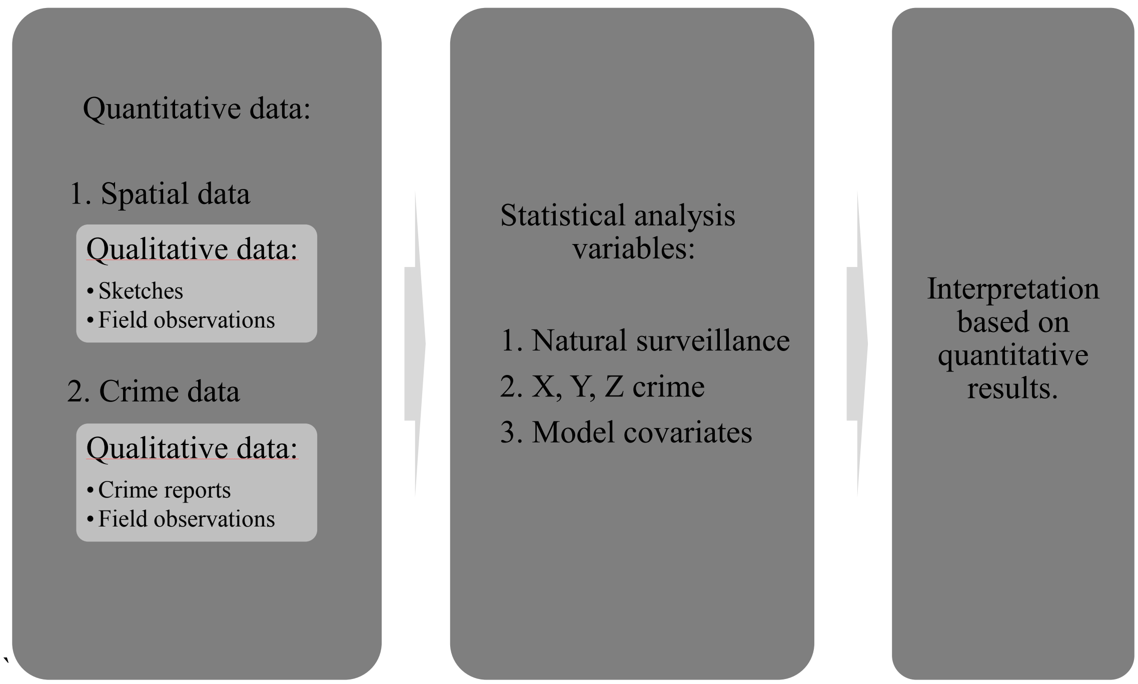

Figure 11. Research design (Source: Author).

3.3 Description of Sample

The city of Spokane, Washington provided the context for this study. Spokane is comprised of 28 neighborhoods and some 166 block groups. One low socioeconomic block group documented as having experienced high burglary rates was chosen for crime-surveillability analysis (See Appendix A for a detailed description of site selection). This purposive sample selection can be justified in two respects; firstly, this study wished to test whether natural surveillance, as one of the main principles of CPTED could be applicable in low socioeconomic-high criminogenic residential areas, and secondly, having a large number of crime commissions facilitated statistical analysis.

The selected study area is located in the West-Central neighborhood of the City of Spokane. The study area extends from Broadway Avenue in south to Sinto Avenue in north and from Ash Street in east to Chestnut and Belt Streets in west. According to the hierarchy of the U.S. Census geographic entities (See *Figure 83*), this area is a block group comprised of 44 census blocks. In addition, 324 parcels and 490 building features are located inside the boundaries of this area. Figure 12 shows the study area as located in the West-Central neighborhood and in the City of Spokane.

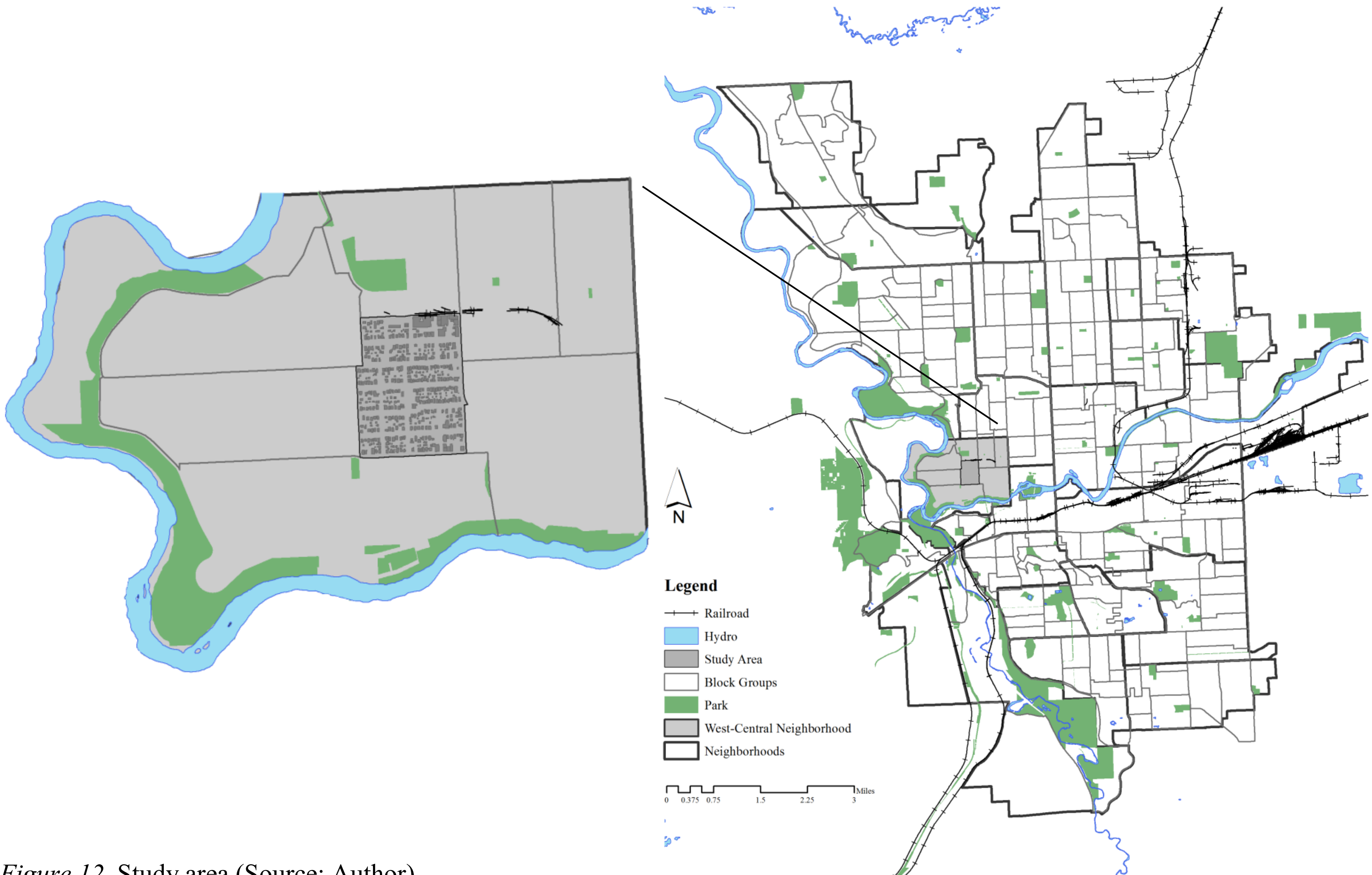

Figure 12. Study area (Source: Author).

3.4 Spatial Data

This section is comprised of three parts; spatial data collection, 2-dimensional georeferencing, and 3-dimensional georeferencing of spatial data. The first section discusses the sources used for gathering and complementing information on spatial data. The second section elaborates on procedures employed to georeference spatial data in ArcMap. The third section explains the techniques utilized to create a 3-dimensional model from 2-dimensional datasets in ArcScene. Procedures employed for collecting and georeferencing spatial data were extremely time-consuming and labor-intensive. It took me approximately a year to collect and georeference spatial data.

3.4.1 Spatial data collection

Oblique aerial imagery constituted the primary source spatial data for this research. The County of Spokane granted me permission to access this data resource for my dissertation. Field observations of architectural and landscape features complemented information extracted from oblique aerial imagery data and were recorded using a digital camera.

3.4.1.1 Oblique aerial imagery

Oblique aerial imagery is captured at an angle making it easier to see and recognize any object on the surface of the earth. Pictometry Inc. (2013) provides oblique aerial imagery captured at a 40 degree angle with the resolution for images set as high as 3-inch Ground Sample Distance (GSD). This fine-grained resolution allows one to zoom into pictures by a fixed amount and see closer views of features on the surface of the earth from north, south, east, west and top views.

The County of Spokane has purchased access to Pictometry oblique aerial imagery. An arrangement with the Spokane County enabled me to use this resource for my research. Pictometry imagery was accessed via a link on a workstation at the Spokane County GIS facility. Metric measurements were performed on Pictometry imagery by using two tools; one measuring horizontal distances and the other vertical heights. Pictometry imagery can be exported in JPEG or other format files. *Figure 13* shows views of Pictometry imagery from north, south, east, west and top for a census block in the study area.

I spent around 70 working days at the Spokane County, and made metric measurements of property features in the study area directly from oblique aerial imagery. In the study area comprising of 44 census blocks, 324 parcels and 490 buildings, detailed information on building features (i.e. buildings, parking garages, and storage sheds), building openings (i.e. doors and windows), vegetation (i.e. street trees, yard trees, bushes and shrubs) and visual barriers (i.e. solid fencing) were collected.

Figure 13. Oblique aerial imagery views for a census block. Source: Pictometry. Reprinted with permission.

In order to collect information on architectural and landscape features, the block group study area was printed on a letter size paper. Unique two digit alphabetical codes were developed for census blocks. Each two adjacent census blocks facing an alley shared the shame first digit of the alphabetic code (See *Figure 14* right). Next, each two adjacent census blocks were printed on a letter or legal size paper (depending on the length of the census blocks). These sheets were used for enumerating buildings and recording information on location, height and type of vegetation and barriers. Numbering of buildings in each two adjacent census blocks started with a two digit number 01 and counted until all buildings were coded (See *Figure 14* left).

Figure 14. Identifiers for census blocks and buildings (Source: Author).

Letter size papers were used for drawing sketches of building facades. The unique identifier for each building and information on land use or building use were recorded on the front top left of each sheet. Sketches were made of north, south, east and west building facades representing information on height of buildings in addition to size and height of building openings (i.e. doors and windows). Sketches were also made on height of garages and storage sheds, but no information on location, size and height of doors or windows to garages or sheds were recoded (See Appendix B for an example of sketches made from Pictometry oblique aerial imagery). Firstly, an assumption was made that no one lives in a garage or a shed and thereby surveillance is not taking place from openings to these structures. And secondly, burglary from garage or storage shed and analyzing visibility from and to doors and windows to garage or storage shed were not part of this study.

In order to collect information on roof types, roof lines and dimensions, building footprints for the study were exported to AutoCAD. Looking at Pictometry top-view images, building roof lines were drafted. Then each two adjacent census blocks were printed on a letter or legal size paper and dimensions of roof lines were measured and recorded by utilizing Pictometry oblique aerial imagery (See Appendix B for an example of drafted roof types and roof lines).

Information on type and height but not crown spread of vegetation features were recorded. Symbols were developed for differentiating between deciduous trees, evergreen trees plants and bushes. Height of vegetation features was recorded next to each symbol. Lastly, height and location of solid fencing features were recorded (See Appendix B for an example of sketches made from Pictometry oblique aerial imagery).

3.4.1.2 Field observations

Oblique aerial imagery does not always provide sufficient information on architectural and landscape features. Weather conditions, location of the sun and the resulting shadow in addition to placements of buildings in respect to each other, density of vegetation features among other factors influence accuracy of data shown by Pictometry oblique aerial imagery. Therefore, additional field observations were conducted to complement and further verify the reliability of the data extracted from Pictometry imagery. In addition, while conducting field observations, I recorded information on building and site maintenance and presence of no-trespassing signs.

Field observations were carried out at multiple times on different days and seasons since some architectural and landscape features could be better depicted at different times. I was accompanied by a friend or a volunteer during field observations. Field observation information was recorded using digital photography. Neighborhood residents approached me on numerous occasions and asked questions regarding the purpose of picture-taking. I explained the purpose of my study, showed my letter of identification if requested, and in some instances residents willingly permitted me to take closer photographs from obscure part of buildings.

For each site survey visit, a site map of the study area with highlights on locations with missing information (i.e. building facades, etc.) was printed on a letter size paper (See Appendix B for an example of sheets taken with me for field observations). Five field observations were conducted in spring and winter seasons each taking between 6 to 8 hours based on availability of natural light. Approximately 2,000 pictures were taken from obscure and random other locations Field observations were repeated until no missing information was found with the exception of information on east side facade to a residential building which had been demolished before the launch of this project. *Figure 15* right shows example of Pictometry imagery for a partially obscured building façade and *Figure 15* left shows a picture taken by me for complementing data on the obscure part.

Figure 15. Oblique aerial imagery versus terrestrial photography. Left: Oblique aerial imagery view of a façade (Source: Pictometry). Right: Terrestrial photography of that same façade (Source: Author).

3.4.2 Georeferencing spatial data

I georeferenced spatial data using ArcGIS 10.0 and 10.1. ESRI ArcGIS Geographic Information System software is offered for educational purposes to students at Washington State University as part of the ESRI Educational site license. I had access to ArcGIS Student 1-year Trial software for three consecutive years. Prior to georeferencing, I set a common coordinate system for data frames and feature classes in ArcGIS.[14] Problems may arise with executing tools

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[14] Feature classes and data frames in this research are all in the State Plane Coordinate System, Zone: Washington North, FIPS Zone: 4601, Datum: NAD83, Unit: Feet (NAD_1983_HARN_StatePlane_Washington_North_FIPS_4601_Feet).

and other tasks in the ArcGIS platform if features are not projected to a common coordinate system.

The following sections explain how I georeferenced spatial data in ArcMap.[15] The first part discusses how building footprints were updated. The second part elaborates on how building openings were mapped. The third part discusses how vegetation and barrier features were georeferenced. And the last part depicts how road centerlines and curblines were transformed into point features.

3.4.2.1 Georeferencing and updating building footprints

Building footprints are drawn to display outline or perimeter of buildings, and do not necessarily display porches or indentations in building facades. Thus, in order to map building openings on building outlines and to create 3-dimensional models for architectural features, I was first required to update building footprints. Measurements from Pictometry oblique aerial imagery helped with updating building footprints.

I first selected building footprints that are completely within the boundaries of the study area and exported them as feature class called "Buildings_StudyArea." I then used two resources to determine which buildings might have been present during the 2006-2010 timeframe[16] Building footprint shapefile as of years 2010 and 2004 are available in the Washington State University GIS & Simulation Lab database. In addition, a 6 inch color aerial imagery covering

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[15] Two-dimensional features for this study were stored in a file geodatabase named "2D_StudyArea.gdb".

[16] This study explored the relationship between natural surveillance and commission of residential burglaries in a five year period between 2006 and 2010.

the Spokane metro area captured in year 2007 is available at the City of Spokane website (City of Spokane, 2013). Analysis of databases showed that three buildings in the study area were constructed sometime between 2004 and 2007. I assumed that these buildings existed in the 2006-2010 timeframe. Seven buildings were demolished between 2004 and 2007. An assumption is made that these buildings did not exist in the study timeframe. One building was replaced by another building but this building had inward looking building openings and its existence or absence did not influence natural surveillance. *Figure 16* shows geographic location of buildings that were constructed or demolished sometime between 2004 and 2007.

Figure 16. Buildings change between 2004 and 2010 (Source: Author).

Editing sessions were started in ArcMap on the "Buildings_StudyArea" layer and polygons representing front, back or side porches were added to this feature class. Polygons were also drawn showing indentations on building façade or outlines. I also modified footprints for garages and added footprints for other building facilities like buildings sheds. *Figure 17* shows changes to a sample of building footprints before and after modification, and *Figure 19* shows updated building footprints in the study area

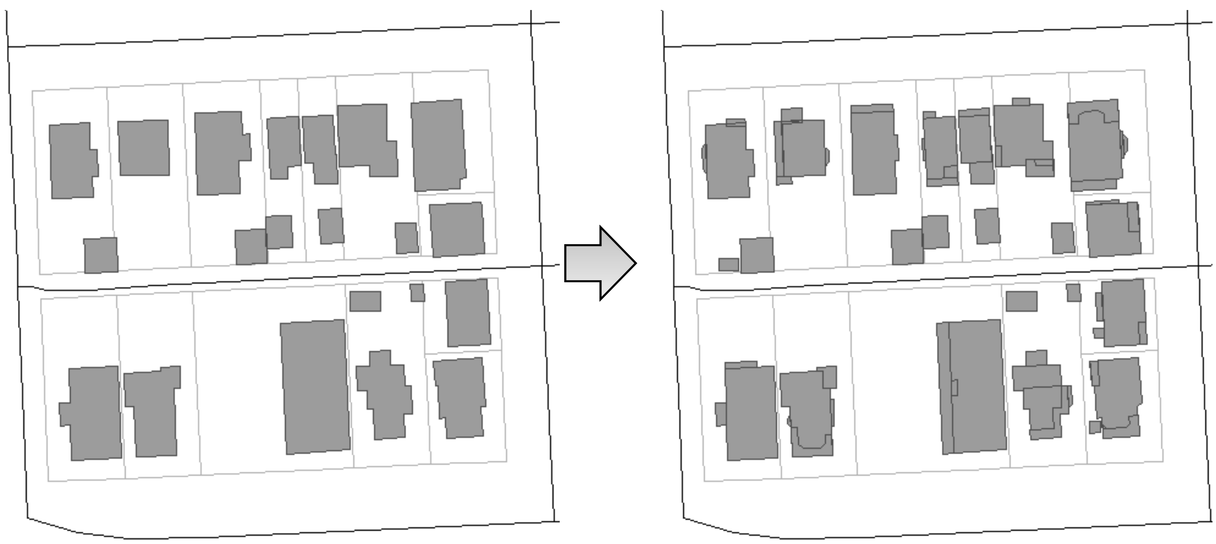

Figure 17. Building footprint modifications (Source: Author).

Unique identifiers were then developed for buildings, garages and sheds. Footprints for buildings, garages and sheds were individually selected, exported and stored as separate feature classes in feature datasets. Feature classes in each census block are stored in a feature dataset. Feature datasets are given the unique two digit alphabetic code of census blocks. The following paragraphs explain how I assigned unique identifiers to buildings, garages and sheds (See *Figure 18*):

- Each building's unique identifier starts with a unique two digit alphabetical code developed for census blocks followed by the two digit numeric code given to each building.
- Identifiers given to garages include building's unique identifier to which garages belong to, followed by underscore character and the letter "P".
- Numbering of sheds is similar to parking garages with the exception that instead of letter "P" letter "S" is used.[17]

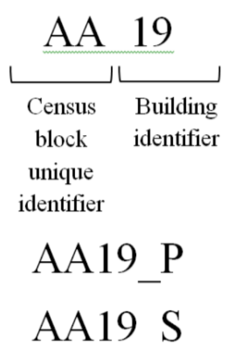

Figure 18. Examples of unique identifiers for buildings, garage and sheds (Source: Author).

I updated or georeferenced 490 building features in 324 parcels in the study area (See *Figure 19*). Along with updating the geometry of buildings, some other information on spatial characteristics of buildings was also recorded. Table 13 shows the name and a brief description for fields computed for the buildings feature class. These fields represent theoretically important characteristics found in the literature to be associated with burglary occurrence.

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[17] In parcels, where more than one parking garage or storage shed belong to a building, other alphabetical letters (i.e. A, B, etc.) followed the underscore character to develop unique identifiers for garages and storage sheds.

Table 13

Tools utilized for creating and adding fields to the buildings feature class (Source: Author).

Tool	Parameters	
Add Field	Field Names	ID_Bldg: 4 digit and letter long unique identifier
		SUM_OC49_SL: possible occupant surveillability within 49 feet
		SUM_OC49_BVBL: occupant surveillability within 49 feet
		SUM_OC95_SL: possible occupant surveillability within 95 feet
		SUM_OC95_BVBL: occupant surveillability within 95 feet
		SUM_OC141_SL: possible occupant surveillability within 141 feet
		SUM_OC141_BVBL: occupant surveillability within 141 feet
		SUM_RD49_SL: possible road surveillability within 49 feet
		SUM_RD49_BVBL: road surveillability within 49 feet
		SUM_RD95_SL: possible road surveillability within 95 feet
		SUM_RD95_BVBL: road surveillability within 95 feet
		SUM_RD141_SL: possible road surveillability within 141 feet
		SUM_RD141_BVBL: road surveillability within 141 feet
		SUM_SW49_SL: possible pedestrian surveillability within 49 feet
		SUM_SW49_BVBL: pedestrian surveillability within 49 feet
		SUM_SW95_SL: possible pedestrian surveillability within 95 feet
		SUM_SW95_BVBL: pedestrian surveillability within 95 feet
		SUM_SW141_SL: possible pedestrian surveillability within 141 feet
		SUM_SW141_BVBL: pedestrian surveillability within 141 feet
		Corner_Lot: yes, no

	Bldg_Face: neighborhood collector, regional
	CornerMiddleT_Lot: corner lot, middle lot, T lot
	Facilities_49 (presence of non-residential facilities within 49 feet distance): yes, no
	Facilities_95 (presence of non-residential facilities within 95 feet distance): yes, no
	Facilities_141 (presence of non-residential facilities within 141 feet distance): yes, no
	Adjacent_Vacant: yes, no
	Maintenance: yes, no
	Trespassing_Sign: yes, no
	Bldg_Use: church; manf; public assembly; residential; retail; service; transportation; unknown; wholesale
	Bldg_Use_Type: 1 unit; 2-4 units; 5 plus units; auto; church; construction; finance; food; generalmerchants; hardware; motor; other; professional; public assembly; unknown; wholesale
	OFFENCE_141 (burglarized): yes, no
	OFFENCETIME_141 (burglarized): daylight, darkness, extended/unknown

Figure 19. 2D building footprints in the study area (Source: Author).

3.4.2.2 Georeferencing building openings

Building openings (i.e. doors and windows) were symbolized with points. Size of building openings were measured from Pictometry oblique aerial imagery. Horizontal and vertical measurements from Pictometry imagery were used to calculate the distance from horizontal and vertical midpoint of openings to the building edge and from the ground accordingly. The horizontal distance measurements were used for placing points on building outlines and vertical distance measurements were stored in a field and later used for creating 3-dimensional point features (See *Figure 20*).

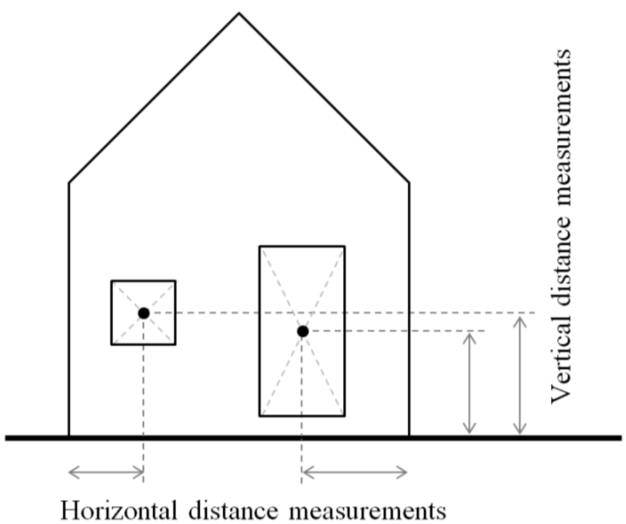

Figure 20. Symbolizing building openings with point features (Source: Author)

Building openings were stored in a point feature class called "Bldg_Opening." Building openings were georeferenced by starting editing sessions on the "Bldg_Opening" and placing points on the outline of building footprints by placing the direction-distance tool on the editor toolbar tool palette. Each point was given a unique identifier. The following paragraphs explain how unique identifiers were developed for building openings (See *Figure 21*):[18]

- Each opening unique identifier starts with a unique two digit alphabetic code given to each census block in the study area;
- The preceding code was followed by a two digit numerical code assigned to the building to which the opening belongs;
- The following letter represents the side on which openings are placed. N, S, W and E abbreviations were used for openings located on North, South, West and East facades;
- The following one digit number after N, S, W or E stands for the floor on which each opening opens to the exterior. Basement openings were coded with number 0. First, second and further floors were coded according to the corresponding one digit number;
- Then, opening types were differentiated by the letters D or W, representing either a door or a window accordingly;
- And lastly, a two digit number is given to each opening. This number starts at 01 and counts until all openings on each side/façade of a building are coded.

[18] After unique identifiers were developed for all openings in our study area, this feature class was exported to excel. The remove duplicates feature was used on the unique identifier's field to determine whether any duplicates existed in the unique identifiers developed for building openings. No duplicates were found.

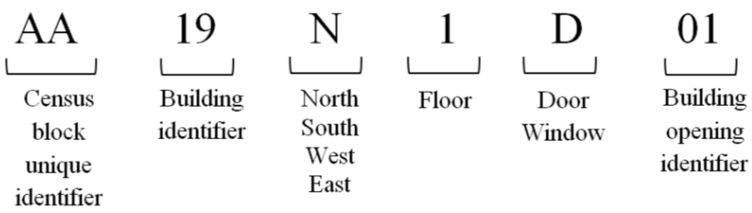

Figure 21. Example of unique identifier for a building opening (Source: Author).

I georeferenced 5,733 points representing building openings in the study area (See *Figure 22*). Along with geocoding locations of building openings, some other information on spatial characteristics of building openings was also recorded. This information represents theoretically important characteristics found in the literature to be associated with burglary occurrence. Table 14 shows the name and a brief description for fields computed for the building openings feature class.

Table 14

Tools utilized for creating and adding fields to the building openings feature class (Source: Author).

Tool	Parameters	
Create feature Class	Feature Class Location	2D_StudyArea.gdb
	Feature Class Name	Bldg_Opening
	Type	POINT
Add Field	Field Names	ID_Opening: 9 digit and letter long unique identifier for building openings
		ID_Bldg: 4 digit and letter long unique identifier for buildings
		ZValue: height of openings from the ground
		Side: north, south, east, west
		Opening_Type: door, window
		Floor: 0, 1, 2, 3
		OC49_SL: possible occupant surveillability within 49 feet
		OC49_BVBL: occupant surveillability within

	49 feet
	OC95_SL: possible occupant surveillability within 95 feet
	OC95_BVBL: occupant surveillability within 95 feet
	OC141_SL: possible occupant surveillability within 141 feet
	OC141_BVBL: occupant surveillability within 141 feet
	RD49_SL: possible road surveillability within 49 feet
	RD49_BVBL: road surveillability within 49 feet
	RD95_SL: possible road surveillability within 95 feet
	RD95_BVBL: road surveillability within 95 feet
	RD141_SL: possible road surveillability within 141 feet
	RD141_BVBL: road surveillability within 141 feet
	SW49_SL: possible pedestrian surveillability within 49 feet
	SW49_BVBL: pedestrian surveillability within 49 feet
	SW95_SL: possible pedestrian surveillability within 95 feet
	SW95_BVBL: pedestrian surveillability within 95 feet
	SW141_SL: possible pedestrian surveillability within 141 feet
	SW141_BVBL: pedestrian surveillability within 141 feet
	Target_141 (target building openings): yes, no
	Territory: Fencing, No Fencing
	Corner_Lot: yes, no
	Opening_Face: alley, building, neighborhood collector, principal, regional, vacant lot
	CornerMiddleT_Lot: corner lot, middle lot, T lot
	Facilities_49 (presence of non-residential facilities within 49 feet distance): yes, no
	Facilities_95 (presence of non-residential facilities within 95 feet distance): yes, no
	Facilities_141 (presence of non-residential facilities within 141 feet distance): yes, no

	Adjacent_Vacant: yes, no
	Maintenance: yes, no
	Trespassing_Sign: yes, no
	Bldg_Use: church; manf; public assembly; residential; retail; service; transportation; unknown; wholesale
	Bldg_Use_Type: 1 unit; 2-4 units; 5 plus units; auto; church; construction; finance; food; generalmerchants; hardware; motor; other; professional; public assembly; unknown; wholesale
	Offence_141 (burglarized): yes, no
	OffenceTime_141 (burglarized): daylight, darkness, extended/unknown

Figure 22. 2D building openings in the study area (Source: Author).

3.4.2.3 Georeferencing vegetation and visual barriers

Vegetation features were stored in a point feature class called "Vegetation." I added three fields to this feature class, representing information on height, type and location of vegetation (See Table 15). Editing sessions were started and plant locations were georeferenced by looking at maps developed by me from Pictometry oblique aerial imagery, pictures taken during site survey visits and a 6 inch color aerial imagery covering the Spokane metro area captured in year 2007. Points were inserted on locations where vegetation trunks are estimated to be situated. I georeferenced 1,629 trees in the study are (See *Figure 23*).

Table 15

Tools utilized for creating and adding fields to the vegetation feature class (Source: Author).

Tool	Parameters	
Create Feature Class	Feature Class Location	2D_StudyArea.gdb
	Feature Class Name	Vegetation
	Type	POINT
Add Field	Input Table	Vegetation
	Field Name	ZHeight: height of plants
	Field Type	Double
	Input Table	Vegetation
	Field Name	Type: bush, deciduous, ponderosa
	Field Type	Text
	Input Table	Vegetation
	Field Name	Description: street, yard
	Field Type	Text

Visual barriers are territorial features that divide public and private space, and obstruct vision. Visual barriers were stored in a line feature class called "Barriers." I added one field to this layer and stored information on height of visual obstructing features (See Table 16). Editing sessions were started, and territorial lines were drawn by looking at maps developed by the author from Pictometry oblique aerial imagery, pictures taken during site survey visits and a 6 inch color aerial imagery covering the Spokane metro area captured in year 2007. Territorial lines were drawn where solid fencing existed. I did not georeference locations of chain link fences because see-through fencing does not obstruct visibility, and I did not need to create 2-dimensional or 3-dimensional models for them. Information on availability of solid and see-trough fencing was stored in a field in the attribute table of the building openings feature class. *Figure 23* shows georeferenced locations of solid fencing in the study area.

Table 16

Tools utilized for creating and adding fields to the barrier feature class (Source: Author).

Tool	Parameters	
Create Feature Class	Feature Class Location	2D_StudyArea.gdb
	Feature Class Name	Barriers
	Type	POINT
Add Field	Input Table	Barriers
	Field Name	Height: height of barriers
	Field Type	Double

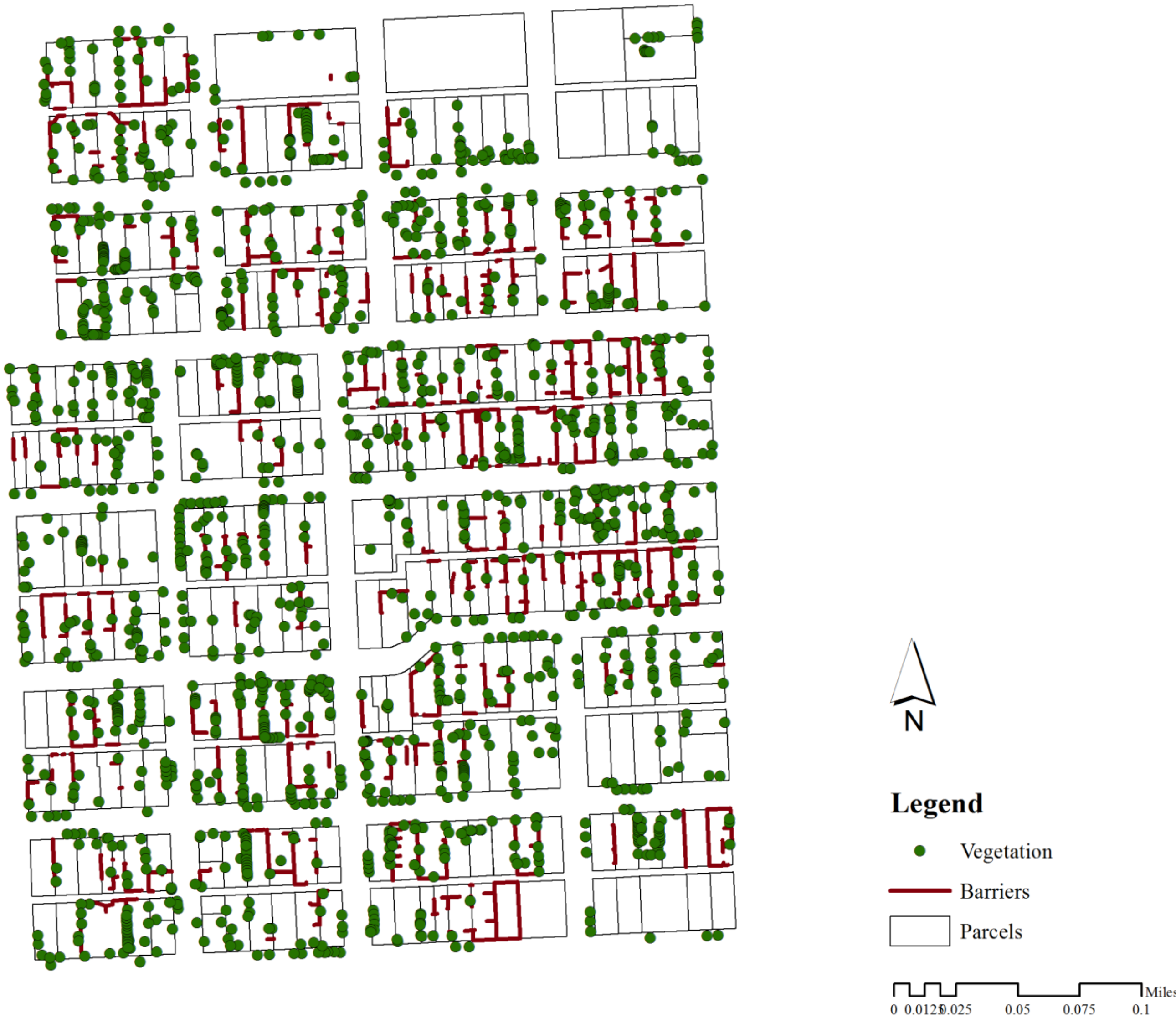

Figure 23. 2D vegetation and visual barriers in the study area (Source: Author).

3.4.2.4 Georeferencing points on road centerlines and curb lines

I represented road centerlines and curblines with points and stored them in point feature classes called "RoadCenterline_Points" and "Sidewalk_Points" respectively. For points placed on road centerlines, an assumption was made that the average length of a car is 15 feet. Editing sessions were started and the construct points tool on the editor toolbar tool palette was utilized to create points at intervals based on the average length of a car along the street centerlines. I also selected additional points to be created at start and end point of street centerlines. In addition, a value of 2.51 feet was calculated for all rows in this point feature class representing the eye height of human beings in the sitting position. That same technique was utilized to create points on curblines, with the difference that I used the length of an average walking stride (62 inches) to create points on curblines. A value of 5.14 feet was assigned to all rows in this point feature class representing the eye height of human beings in the standing position. Table 17 shows procedure employed to create points on road centerlines and curblines and *Figure 24* shows georeferenced points on road centerlines and curblines.

Table 17

Tools utilized for creating and adding fields to the road centerlines and curb lines point feature class (Source: Author).

Tool	Parameters	
Create Feature Class	Feature Class Location	2D_StudyArea.gdb
	Feature Class Name	RoadCenterline_Points/ Sidewalk_Points
	Type	POINT
Add Field	Input Table	RoadCenterline_Points/ Sidewalk_Points
	Field Name	ZHeight: eye height in sitting or standing position
	Field Type	Double

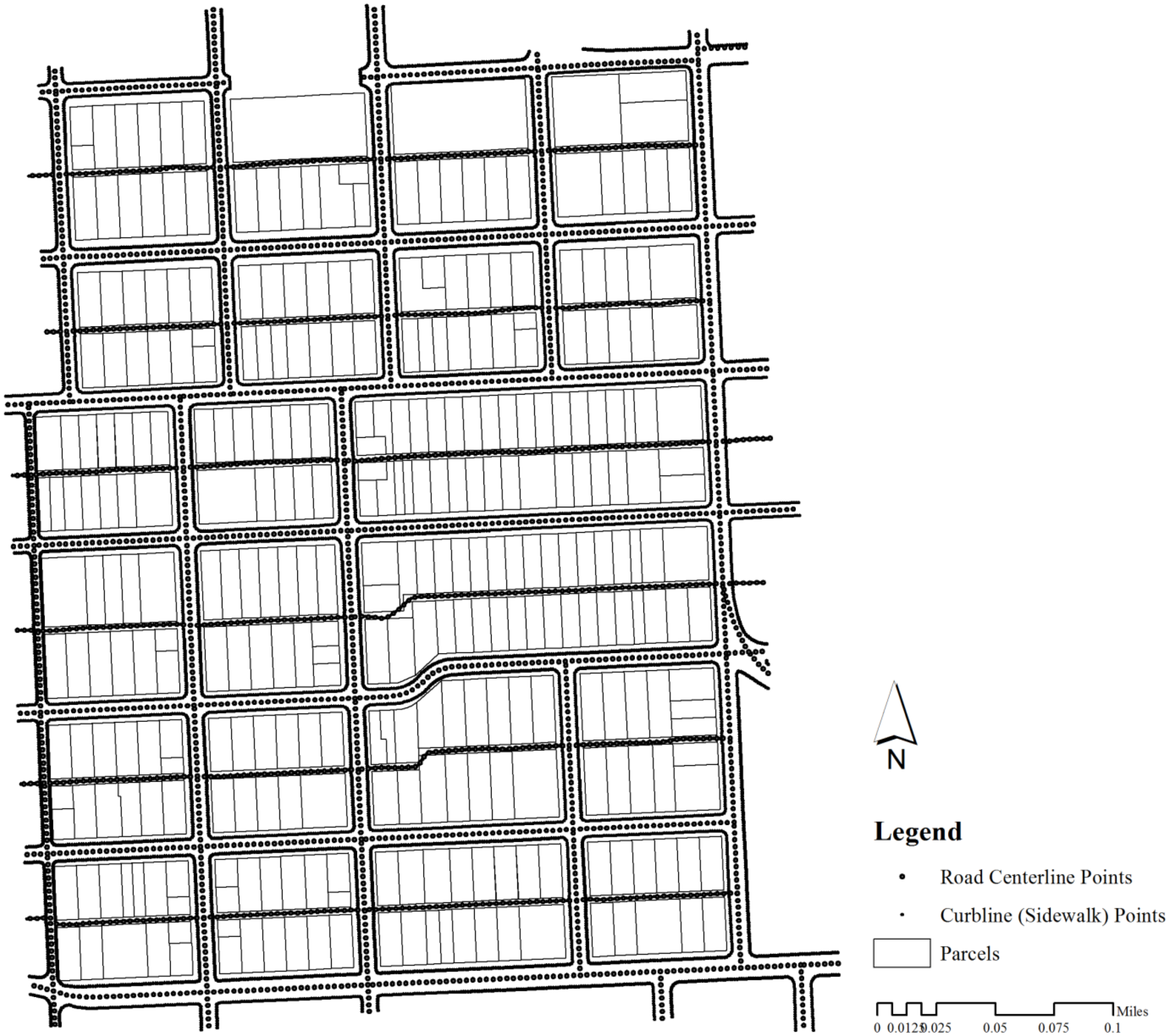

Figure 24. 2D road centerline points and curbline points in the study area (Source: Author).

Figure 25. 2D architectural and landscape features in the study area (Source: Author).

3.4.3 Three-dimensional visualization of spatial data

Various technologies (i.e. LiDAR, 3D stereo or digital photogrammetry, etc.) or software (i.e. CityEngine, LandSim3D etc.) exist for generating 3-dimensional cities. I chose to manually create a 3-dimensional model of the study area in the ArcScene platform because other solutions were very costly, not publically available, encompass a steep learning curve or necessitate further processing and interpretation of datasets. The following sections explain procedures employed for creating 3-dimensional models for surface morphology, buildings, building openings, vegetation, visual barriers, street centerline and curbline points.[19]

3.4.3.1 TIN for the West-Central neighborhood

The first step in creating a 3-dimensional model of an area is to generate its surface morphology. Triangulated irregular network (TIN) models and digital elevation models (DEM) are representations of surface morphology in form of vector or raster-based digital geographic data. Triangulated irregular network models (TIN) are vector-based geographic data representing earth's morphology through triangulated vertices. In these models, vertices are connected through a series of adjacent, non-overlapping and different sized triangles. Triangles have unique slopes and geometries capturing and representing the manufactured or natural geography of the earth (Esri, 2014a).

In digital elevation models (DEM), raster-based digital geographic data represent surface morphology. Thus, DEMs are a "… compact way of storing 3D information using a 2D matrix of

[19] 3-dimensional spatial data are stored in a geodatabase named "3D_StudyArea.gdb."

elevation values…" on regular grids of the earth's surface (Ratti, 2005, p. 547). In DEMs, information on z-values is stored in regularly spaced pixels and retrieved in shades of gray as a digital image. *Figure 26* top shows a triangulated irregular network model (TIN) and *Figure 26* bottom shows a digital elevation model (DEM) for the study area.

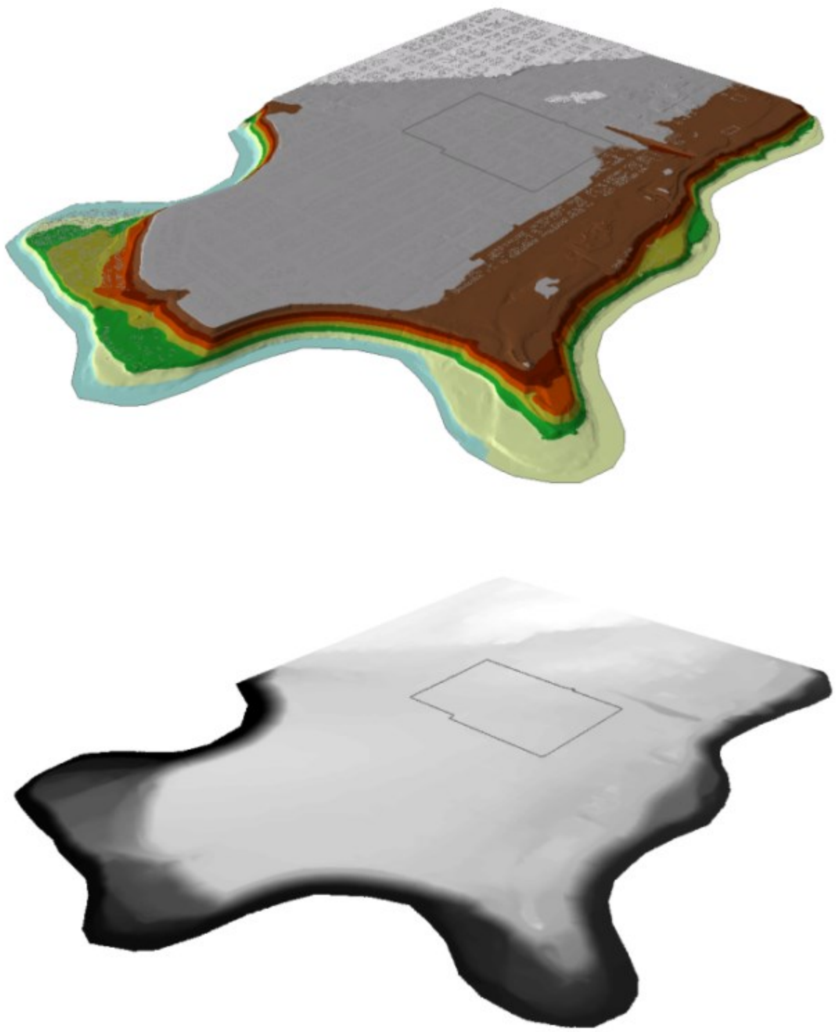

Figure 26. Representations of surface morphology. Top: TIN. Bottom: DEM (Source: Author).

TIN surface models can be created from point, line or polygon features containing elevation information. To create an accurate TIN surface model, topographic contour data with 2 feet intervals was utilized . To capture discontinuity on surface of the TIN, road polygons were introduced as hard breaklines. And to define and clip the boundary of the TIN, a polygon boundary of the West-Central Neighborhood was used (See Table 18). Shapefiles for road polygons and neighborhood boundaries in the city of Spokane were available in the Washington State University GIS & Simulation Lab database. Contour data were downloaded from the City of Spokane's website (City of Spokane, 2013).

Table 18

Tools utilized for creating a TIN (Source: Author)

Tool	Parameters			
Create TIN	Output TIN	TIN_WestCentral		
	Coordinate System	NAD 1983 HARN StatePlane Washington North FIPS 4601 Feet		
	Input Features	Height Field	Surface Type	Tag Field
	Contour lines	ELEV	Mass_Points	None
	Road Polygon	None	Hard_Line	None
	West_Central	None	Soft_Clip	None

Building footprints cannot be introduced in the first step of creating TIN models because footprints do not have elevation values. Therefore, to create flat pads for building footprints upon which three dimensional models of buildings, garages and sheds can later sit, elevation statistics for building footprints were calculated and added to the TIN model. To determine elevation statistics for building footprints, the primary TIN was exported to a raster dataset by using the TIN to raster tool. When TIN models are converted to DEMs, some loss of information may occur depending on the resolution set in the export tool. In order to have the DEM of the West-Central neighborhood closely represent the TIN model and not to lose elevation statistics on building footprints, the number of cells on the longest side of the DEM was set at 5000 (See Table 19).

Table 19

Tools utilized for creating a DEM (Source: Author).

Tool	Parameters	
TIN to Raster	Input TIN	TIN_WestCentral
	Output Raster	DEM_ WestCentral
	Sampling Distance	OBSERVATIONS 5000

Zonal statistics as table tool was then utilized to calculate elevation statistics for building footprints. This tool generated an output table representing basic descriptive statistics (i.e. mean, maximum, minimum, etc.) for building footprints based on the data stored in the DEM file. Utilizing this tool, values of raster cells circumscribed within each building footprint were summarized within the zone of each building footprint, meaning that cells belonging to a certain footprint were assigned similar elevation values. This table was joined to the buildings feature class (Buildings_StudyArea), followed by editing the original TIN with elevation values for building footprints. Employing these techniques, flat pads were created on surface of the TIN model enabling 3-dimensional models of buildings to be placed on flat surfaces (See Table 20). *Figure 27* left shows part of a TIN model with no information on elevation values for building footprints and *Figure 27* right represents that same part of a TIN model after introduction of elevation values for building footprints.

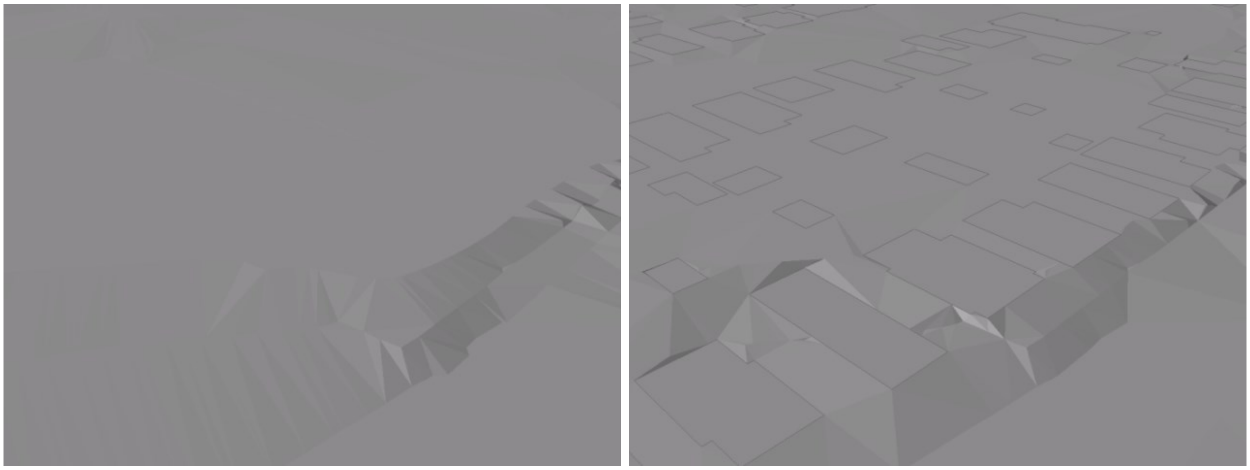

Figure 27. Creating flat pads for building footprints. Left: TIN before introducing flat pads. Right: TIN after introducing flat pads (Source: Author).

Table 20

Tools utilized for calculating elevation statistics for building footprints and editing the TIN model (Source: Author).

Tool	Parameters			
Zonal Raster or Feature Zone Data	Input Raster or Feature Zone Data	Buildings_StudyArea		
	Zone Field	BuildingID		
	Input Value Raster	DEM_WestCentral		
	Output Table	ZonalStat_Bldg		
Add Join	Layer Name or Table View	Buildings_StudyArea		
	Input Join Field	BuildingID		
	Join Table	ZonalStat_Bldg		
	Output Join Field	BuildingID		
Edit TIN	Output TIN	TIN_WestCentral		
	Coordinate System	NAD 1983 HARN StatePlane Washington North FIPS 4601 Feet		
	Input Features	Height Field	Surface Type	Tag Field
	Buildings_StudyArea	Mean	Soft_Replace	None

3.4.3.2 Three-dimensional building features

To create 3-dimenional features for buildings, building footprints were first draped on the West-Central TIN model. Footprints were then extruded according to their height on the extrusion tab from the layer properties panel. Building features having given height properties were converted to 3D Multipatch features via the layer 3D to feature class tool. 3-dimensional Multipatch features were extruded polygons and did not display information on porches or facade indentation. Therefore, 3-dimensional Multipatch features were exported as Collada files for further editing in Google SketchUp. Collada files were edited in Google SketchUp and exported back to ArcScene (See Table 21).

Table 21

Tools utilized for creating 3D building Multipatch features (Source: Author).

Tool	Parameters	
Layer 3D to Feature Class	Input Feature Layer	Unique identifier for buildings (i.e. AA18)
	Output Feature Class	Unique identifier for buildings_F (i.e. AA18_F)
Multipatch to Collada	Input Multipatch Features	Unique identifier for buildings_F (i.e. AA18_F)
	Output Collada Folder	Unique identifier for buildings_F_C (i.e. AA18_F_C)

Google SketchUp Pro 2012 student version is utilized for editing building Collada files in this research. Collada files were imported in Google SketchUp one by one. Building geometries, facades and roofs were then modeled with information collected from Pictometry oblique aerial imagery and field observations. If no data on building height were available, height estimations were made based on window heights or height of nearest features in that façade. SketchUp files were exported as new 3-dimensional Collada files. Lastly, editing sessions were started in ArcScene and the edit placement tool on the editor toolbar was utilized to replace simple 3-dimensional Multipatch features with the 3-dimensional models edited in SketchUp (See *Figure 28*).

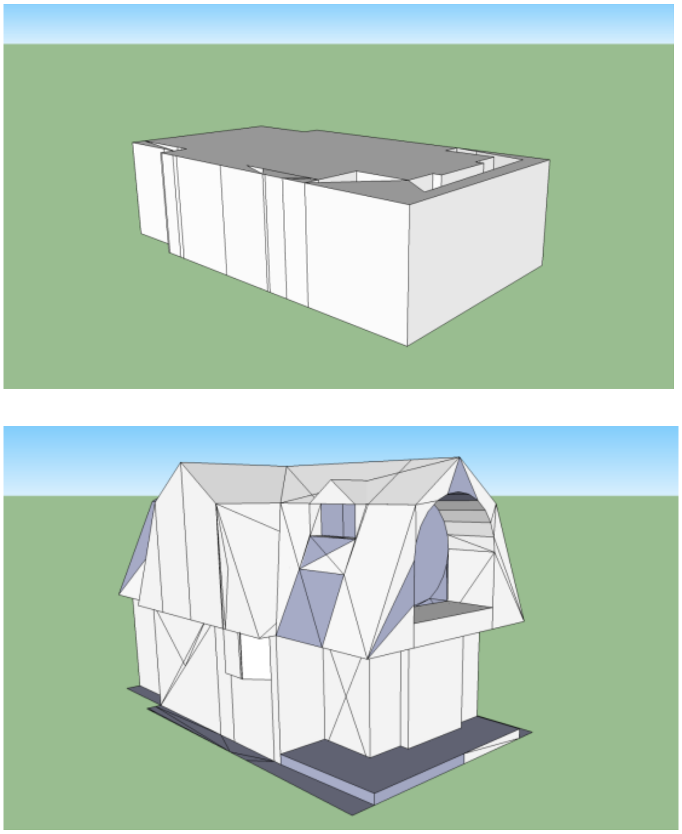

Figure 28. 3D buildings in ArcScene and Google SketchUp. Top: 3D Multipatch building features created in ArcScene. Bottom: 3D Multipatch building features edited in Google SketchUp (Source: Author).

I was required to create frames around 3-dimensional building openings.[20] To this end, I first created 3-dimensional buffers around 3-dimensional building openings by utilizing the buffer 3D tool. I then intersected 3-dimensional buffers with building Multipatch features via the intersect tool. The buffer 3D tool was used again to create a smaller 3-dimensional buffer around 3-dimensional building openings. Lastly, I removed portion of the intersected Multipatch feature that overlapped with the smaller 3-dimensional buffers (See Table 22 and *Figure 29*).

[20] The reason for creating frames around building openings is explained in the ModelBuilder chapter of the dissertation.

Table 22

Tools utilized for creating frames around 3D building openings (Source: Author).

Tool	Parameters	
Buffer 3D	Input Features	Bldg_Opening_3D
	Output Feature Class	Bldg_Opening_3D_Buffer5
	Distance	.5
Intersect 3D	Input Multipatch Features	Bldg_3D
	Output Feature Class	Bldg_Opening_3D_Buffer5_Intersect
Buffer 3D	Input Features	Bldg_Opening_3D
	Output Feature Class	Bldg_Opening_3D_Buffer4
	Distance	.4
Difference 3D	Input Features	Bldg_Opening_3D_Buffer5_Intersect
	Subtract Feature Class	Bldg_Opening_3D_Buffer4
	Output Feature Class	Bldg_Opening_3D_Buffer5_Difference

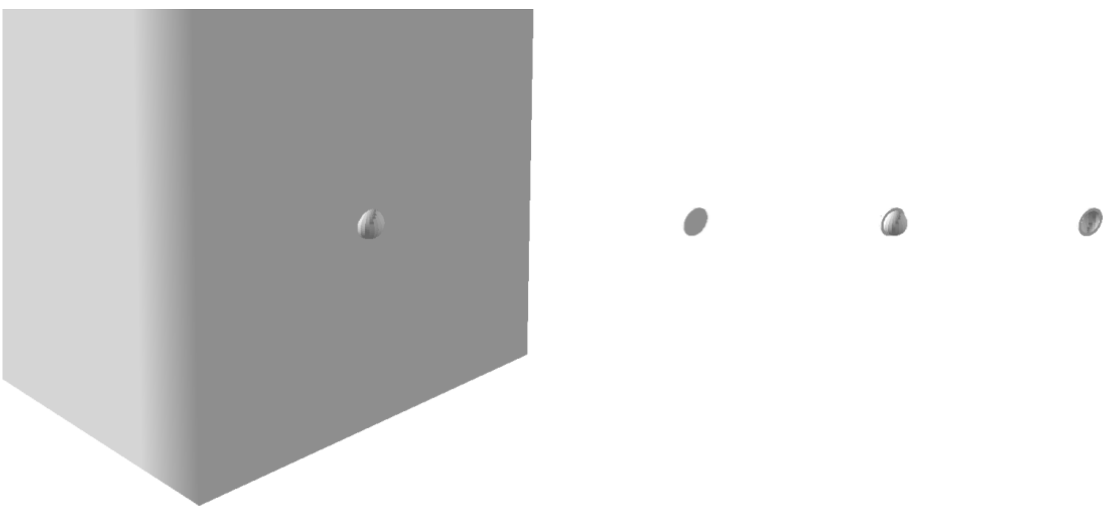

Figure 29. Creating frames around 3D building openings (Source: Author).

In the last step, I combined 3-dimensional Multipatch features for buildings (i.e. buildings, garages, storage sheds and opening frames) via the merge tool. *Figure 30* shows a perspective view of 3-dimensional building features in the study area.

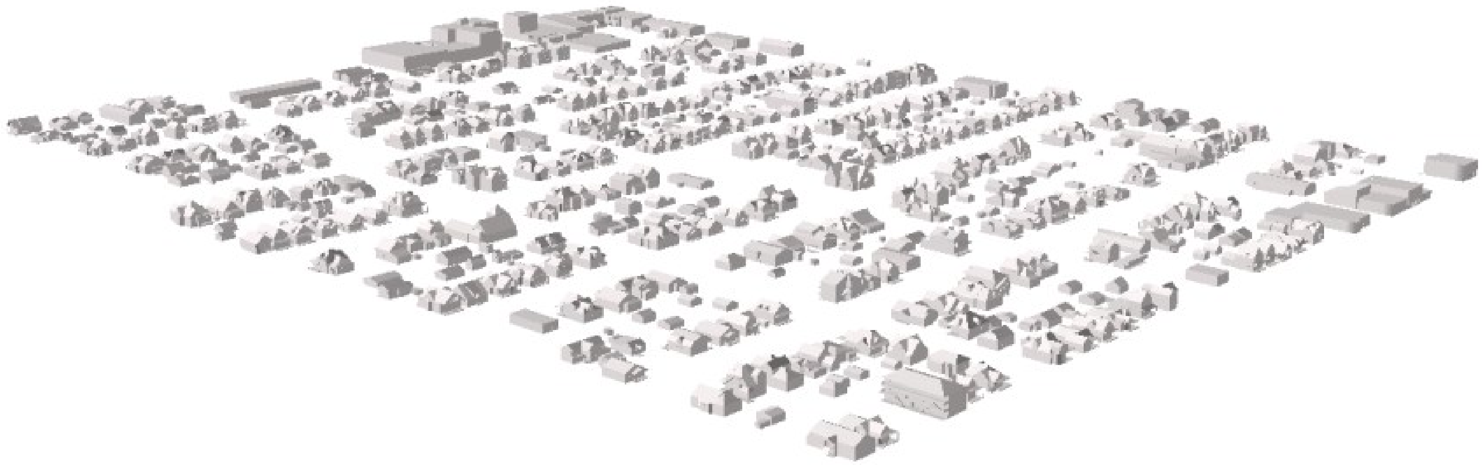

Figure 30. 3D building Multipatch features in the study area (Source: Author).

3.4.3.3 Three-dimensional building openings

3-dimensional point features could not be draped on TIN surfaces as polygon features (i.e. footprint), instead point features (building openings, vegetation, street centerline and curbline points) could be generated by taking height values from the attribute table of the point feature class. Two tools were utilized for creating 3-dimensional point features for building openings; (a) add surface information tool and (b) feature to 3D by attribute tool. Add surface information tool interpolated or derived spot elevation values (Z) from building openings XY locations on the West-Central TIN. Next, I created a new field and used the calculate field tool to sum spot elevation values (Z) and midpoint height value of building openings (ZValue). Feature to 3D by attribute tool was then utilized to create 3-dimensional point features by taking height values (ZValue_Z) from the attribute table of the Bldg_Opening feature class (See Table 23). *Figure 31* shows georeferenced three-dimensional point features for building openings.

Table 23

Tools utilized for creating 3D building openings point features (Source: Author).

Tool	Parameters	
Add Surface Information	Input Feature Class	Bldg_Opening
	Input Surface	TIN_WestCentral
	Output Property	Z
Add Field	Input Table	Bldg_Opening
	Field Name	ZValue_Z
	Field Type	Double
Calculate Field	Input Table	Bldg_Opening
	Field Name	ZValue_Z
	Expression	ZValue_Z = [Z] + [ZValue]
Feature To 3D By Attribute	Input Features	Bldg_Opening
	Output Feature Class	Bldg_Opening_3D
	Height Field	ZVlaue_Z

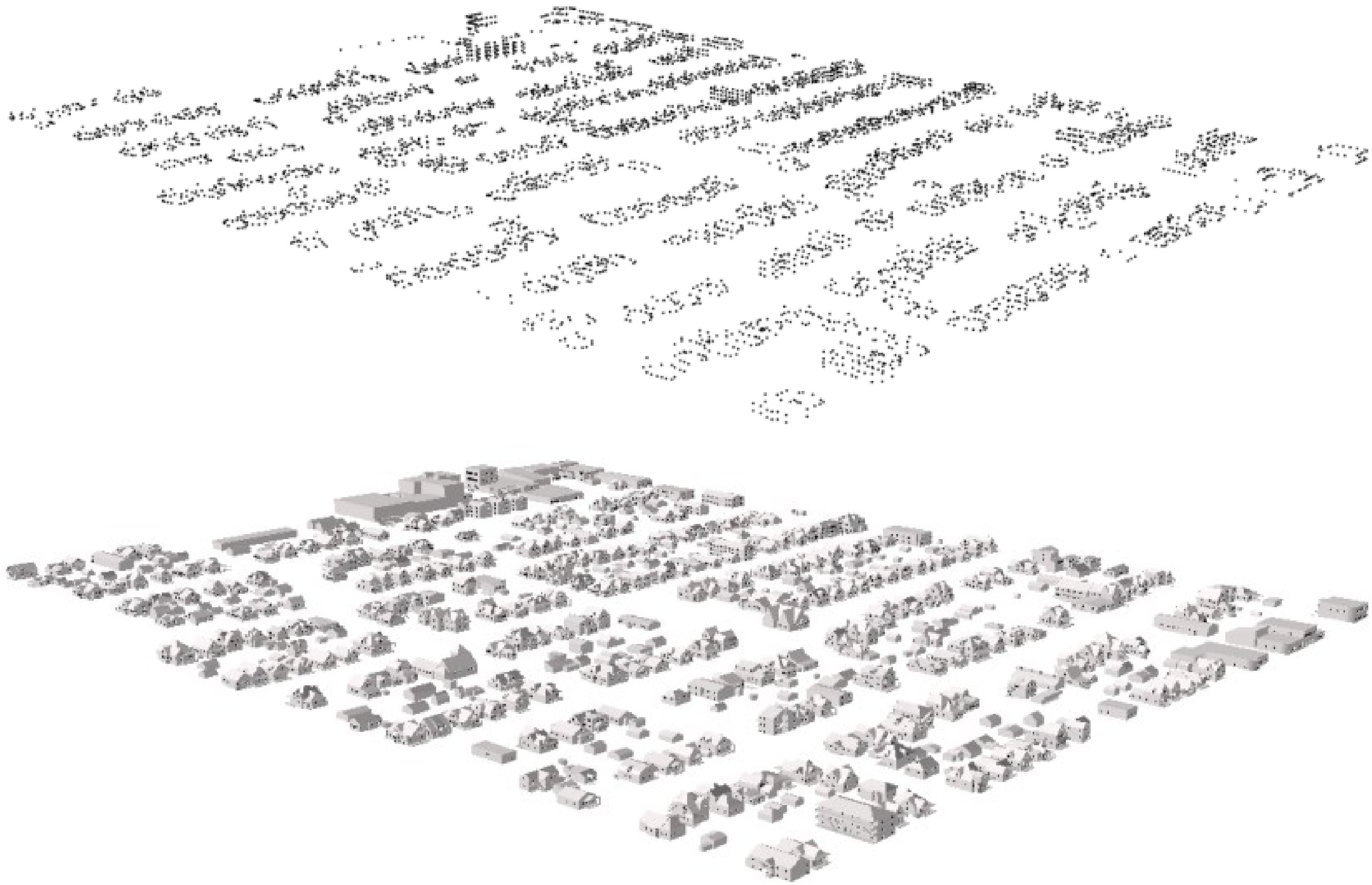

Figure 31. 3D building openings point features in the study area (Source: Author).

3.4.3.4 Three-dimensional vegetation features

A series of tools and procedures were utilized to created 3-dimensional features representing vegetation in the study area. The add surface information tool was used to derive spot elevation values (Z) from vegetation XY location on the West-Central TIN, followed by the feature to 3D by attribute tool to project plants on the surface of the TIN according to spot elevation values (See Table 24).

Table 24

Tools utilized for deriving spot elevation values for vegetation from the TIN model and projecting vegetation features on the TIN (Source: Author).

Tool	Parameters	
Add Surface Information	Input Feature Class	Vegetation
	Input Surface	TIN_WestCentral
	Output Property	Z
Feature to 3D by Attribute	Input Features	Vegetation
	Output Feature Class	Vegetation_3D
	Height Field	Z

3-dimensional graphics closely representing vegetation in the block group study area were chosen from the ArcScene symbol selector panel (See *Figure 32*). In each census block, subsets of 3-dimensional point features were created for different types and heights of vegetation. The symbology and height of 3-dimensional vegetation point features were modified on the symbol properties panel of the corresponding 3-dimensional graphics. Next, the layer to 3D feature class was used to create 3-dimensional Multipatch features from 3-dimensional graphics (See Table 25). Lastly, 3-dimensional Multipatch vegetation features were combined via the merge tool.

Figure 32. 3D graphics from the ArcScene symbol selector panel for evergreen trees, deciduous trees, bushes and shrubs (Source: Author).

Table 25

Tool utilized for creating 3D vegetation Multipatch features (Source: Author).

Tool	Parameters	
Feature to 3D by Attribute	Input Feature Layer	Unique census block identifier_Vegetation_3D_Type_Height
	Output Feature Class	Unique census block identifier_Vegetation_3D_Type_Height_F

Later, I noticed 3-dimensional graphics in ArcScene were made up of 2-dimensional surfaces circumscribed in rectangular prism volumes. Therefore, in case of vegetation features, the rectangular prism volume was considered a plant instead of volumes created by tree trunk, branches and leaves. This caused concerns for visibility analysis since sightlines were considered invisible when they hit faces of rectangular volumes. However, vegetation obstruct smaller volumes (See *Figure 33*).

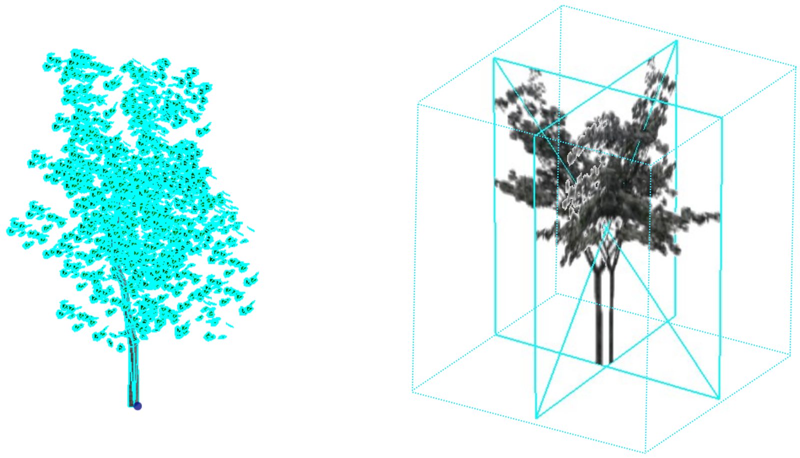

Figure 33. Vegetation volume. Left: Volume of a tree created by tree trunk, branches and leaves. Right: Volume of a tree created by rectangular prism volume of 2D graphics is ArcScene (Source: Author).

To overcome this issue, I downloaded 3-dimensional vegetation models composed of stems, branches and leaves from the SketchUp 3D warehouse. 3-dimensional vegetation models were selected for evergreen trees, deciduous trees, bushes and shrubs (See *Figure 34*). SketchUp files were edited according to height of vegetation features in the study area, and Collada files were created for various types and heights of vegetation features.

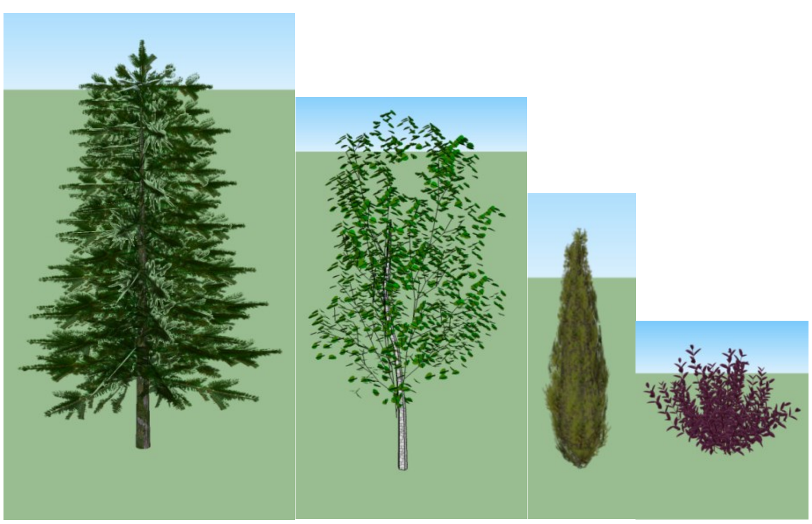

Figure 34. 3D models for vegetation from SketchUp 3D warehouse for evergreen trees, deciduous trees, bushes and shrubs (Source: Author).

Lastly, I edited the "VEG" Multipatch feature class by starting editing sessions in ArcScene, and utilizing edit placement tool on the editor toolbar for replacing ESRI 3-dimensional Multipatch features with the SketchUp 3-dimensional Collada files. I created two subset feature classes from the vegetation Multipatch feature class (VEG); one having 3-dimensional Multipatch vegetation features located on streets (VEG_STREET), and the other including 3-dimensional Multipatch vegetation features planted in yards (VEG_YARD). *Figure 35* shows a perspective view of 3-dimensional vegetation features in the study area.

Figure 35. 3D vegetation Multipatch features in the study area (Source: Author).

3.4.3.5 Three-dimensional barrier features

Visual barrier line features could be draped on TIN surface models from the layer properties panels similar to polygon features. Visual barrier lines were then extruded according to their height values previously stored in the attribute table of the "Barriers" feature class. The layer to 3D feature class tool was then utilized for creating 3-dimensional Multipatch features from the barrier feature class (See Table 26). *Figure 36* shows a perspective view of georeferenced 3-dimensional visual barriers features in the study area.

Table 26

Tools utilized for creating 3D visual barrier Multipatch features (Source: Author).

Tool	Parameters	
Layer 3D to Feature Class	Input Feature Layer	Barriers
	Output Feature Class	Barriers_3D_F

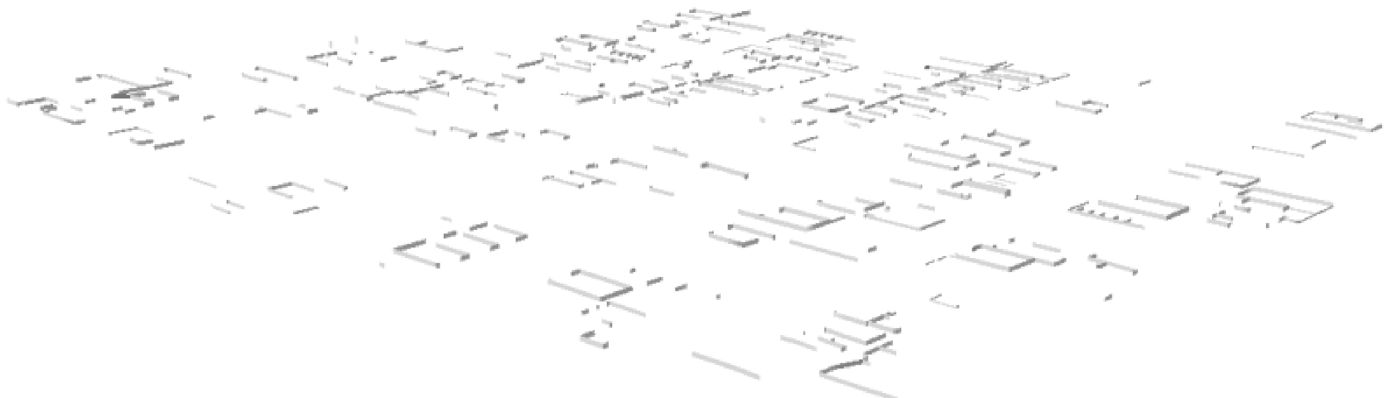

Figure 36. 3D visual barrier Multipatch features in the study area (Source: Author).

3.4.3.6 Three-dimensional street centerline and curbline points

Similar to building openings, I used two tools for creating 3-dimensional centerline and curbline point features; (a) add surface information tool and (b) feature to 3D by attribute tool. I derived spot elevation values (Z) from street centerline and curbline points XY locations on the West-Central TIN. I then summed spot elevation values (Z) with eye height values of human beings in the sitting (for road centerline points) and standing position (for curbline points) in a new field. Lastly, the feature to 3D by attribute tool was utilized to create 3-dimensional point features by taking height values (ZH_Z) from the attribute table of the street centerline (RoadCenterline_Points) or curbline points (Sidewalk_Points) feature class (See Table 27). *Figure 37* shows a perspective view for the georeferenced three-dimensional Multipatch features for road centerline and curbline points in the study area

Table 27

Tools utilized for creating 3D road centerline and curbline point features (Source: Author).

Tool	Parameters	
Add Surface Information	Input Feature Class	RoadCenterline_Points/ Sidewalk_Points
	Input Surface	TIN_WestCentral
	Output Property	Z
Add Field	Input Table	RoadCenterline_Points/ Sidewalk_Points
	Field Name	ZH_Z
	Field Type	Double
Calculate Field	Input Table	RoadCenterline_Points/ Sidewalk_Points
	Field Name	ZH_Z
	Expression	ZH_Z = [Z] + [ZH]
Feature To 3D By Attribute	Input Features	Bldg_Opening
	Output Feature Class	Bldg_Opening_3D
	Height Field	ZH_Z

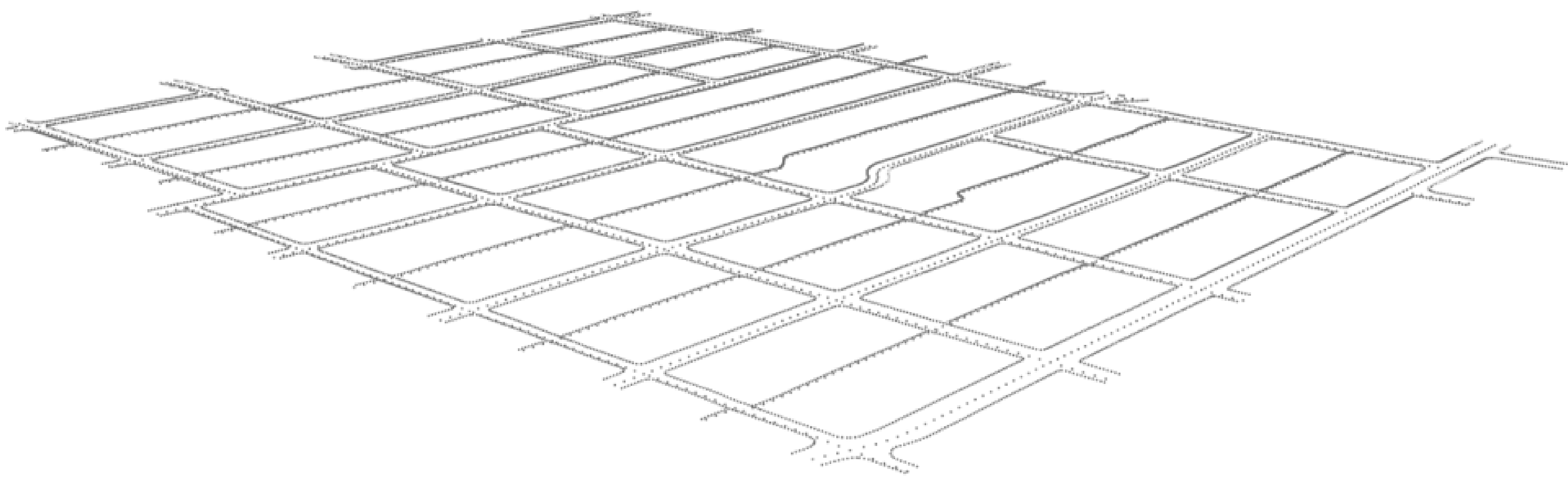

Figure 37. 3D road centerline and curbline point features in the study area (Source: Author).

Figure 38. 3D architectural and landscape Multipatch features in the study area (Source: Author).

3.5 Residential Burglary Crime Data

This section is comprised of three sections; crime data collection, informational elements of crime reports and geocoding crime data. The first section discusses the sources utilized for gathering and complementing information on crime data. The second section elaborates on variables collected and developed from burglary reports. The third section explains the techniques utilized to geocode location of residential burglaries.

3.5.1 Crime data collection

Residential burglary crime reports were studied for a 5-year period from January 1, 2006 through December 31, 2010. I collected crime data in compliance with protocols approved by the Spokane Police Department and the Washington State University. The Spokane Police Command Staff granted me access to the Spokane Police Department's burglary reports for my doctoral studies. This approval was based on a basic background check and signing a memorandum of understanding (MOU) or confidentially agreement between me and the Spokane Police Department. In addition, I submitted the human subject application for non-exempt research activities to the Institutional Review Board (IRB) at Washington State University (WSU). WSU requires the principal investigator to be a WSU faculty; therefore, IRB application was submitted with the support of the dissertation committee chair as the principal investigator. After an expedited review, the Institutional Review Board (IRB) determined that my research qualifies for exemption.[21]

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[21] The Washington State University Institutional Review Board reference number assigned to the certification of exemption is 12903.

3.5.1.1 Crime reports

I provided a georeferenced shapefile outlining the study area to crime analysts at the Spokane Police Department. Residential burglaries occurred in the study area for years 2006, 2007, 2008, 2009 and 2010 were separately queried by crime analysts at the Spokane Police Department. Five sheets including incident numbers and locations were provided to me. I used incidents numbers for retrieving and studying crime reports on a workstation at the Spokane Police Department crime analyst facility.

Crime incident reports were prepared by officers at the Spokane Police Department for non-research purposes. Therefore, it was hard to ensure the quality of collected data. There were instances that no crime reports could be retrieved for an incident number. There were occasions that two reports were most likely prepared for one incident. There were also cases that commercial burglaries were categories as residential burglaries.

In addition, information was generally missing on spatial characteristics of crime sites. Furthermore, information collected on spatial characteristics of crime sites were not consistent, for instance multiple victimized sites were recorded having different spatial characteristics that were unlikely to have been altered in the timeframe between incidents. Moreover, variations existed among informational elements collected. Differences can be explained in two respects; firstly, several incident report types were utilized for reporting crimes. I came across three different incident report types even in a year. Secondly, while some officers were very precise in collecting and reporting crime data, some others provided a general incident report.

3.5.1.2 Field observations

There were instances in which a specific door or window to a dwelling (i.e. door or window to unit A) was reported to have been used for a burglary entry point. However, my existing data (i.e. Pictometry oblique aerial imagery and pictures taken from architectural features) could not show which unit is A. Therefore, I conducted additional field observations to determine burglaries point of entry by taking pictures of burglarized dwellings. In some cases even after field observations, unit A to a building could not be located because doors to apartment dwellings are not labeled with the corresponding unit number.

3.5.2 Informational elements of residential burglary crime

Residential burglary reports contain information on demographic characteristics of victims, suspects (if known) and crime sites. Several informational elements were thought to be valuable and extracted from crime reports for this study. I collected information on; (1) address, (2) point of entry, (3) incident date and time, (4) security, (5) type of premise (6) method of entry and (7) demographic characteristics of victims. Each informational element of residential burglaries is discussed below.

3.5.2.1 Address

I recorded information on address of burglarized dwellings. Address of burglarized properties is always transcribed. However, I come across the following concerns regarding address of burglarized dwellings:

- Address of burglarized dwelling appeared twice in incident forms; once as location of incident and once in the summary provided by officers for further clarifications. In some cases, discrepancies existed between these two addresses. Nevertheless, in most cases this discrepancy didn't raise a concern. But in the time frame of this study, one building opening in the study area could not be geocoded because the address of the burglarized building could be matched to two residences in the same premise. This issue may have risen because of typo errors when automating crime reports.
- Address of burglarized properties was in most occasions accompanied by zip code. Zip code can play an important role in geocoding locations of crimes if transcribed. However, zip codes of victimized properties were not always correctly transcribed. This issue did not raise a concern for the study but may raise difficulties if larger areas were subject of research. For instance same address but different zip codes may differentiate between two buildings located in different parts of a city.

3.5.2.2 Point of entry

I recorded information on entry point of burglaries. Even though a burglary's point of entry was required to be included in a report (if known), not all entry points were precisely coded or communicated. I came across the following concerns in reporting entry point of burglaries:

- If a door was used as entry point, the exact location or unit was provided by most officers for reporting purposes. However, some cases were found in which the entry point was briefly stated as back door while more than one door existed in the back of the burglarized building.

- If a burglary entry point was through a window, phrases like west side window, kitchen window, bedroom window, among others were mostly used for reporting a burglary point of entry. Typically, more than one window is placed on a building façade or a building; therefore, I was unable to geocode burglaries through windows if their geographical location were not clearly communicated. Nevertheless, I came across several incident reports that officers tried their best to exactly communicate the location of targeted windows.

Lastly, I would have liked to complete the missing information by inquiring officers for the exact point of burglaries on burglarized sites. However, I couldn't approach the officers and ask for burglaries entry points because according to crime analysts at the Spokane Police Department, officers usually respond to several incidents per week. Thus, inquiring about a crime which was taken place between 3-8 years ago appeared to be unrealistic.

3.5.2.3 Incident date and time

I used two informational elements from burglary reports to create a variable called the "estimated range of time of offence" (Eck, 1979). Estimated time of residential burglary occurrence is the time period during which burglary occurs, and is based on victim's knowledge of time leaving and returning to the burglarized property. All burglary crime reports except for one case had complete information on the last date and time victims were in premise and the date and time they returned to that premise and reported the burglary.

In order to determine whether estimated range of time of burglary incidents were in daytime, nighttime, civil twilight or unknown hours, the complete sun and moon rise and set information for days in which burglaries occurred were extracted from the United States Naval Observatory website (United States Naval Observatory, 2012). Providing date and location (See *Figure 39*), a table with sun and moon data for days in which a burglary occurred is retrieved. This table shows information on sunrise, sunset and begin and end of civil twilight times (See *Figure 40*).

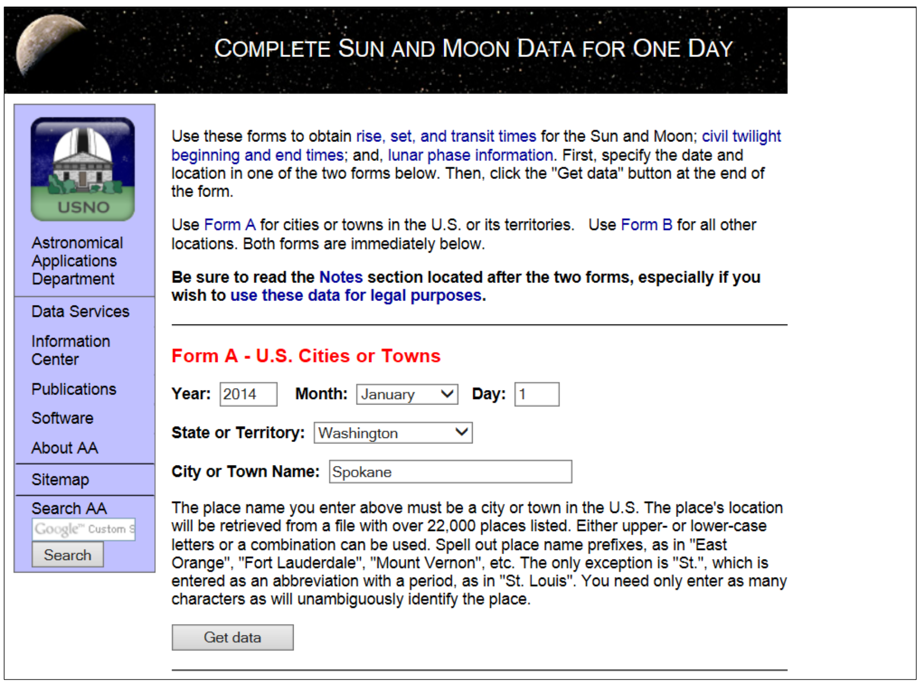

Figure 39. Complete sun and moon data retrieval tool. Retrieved from the United States Naval Observatory website: http://aa.usno.navy.mil/data/docs/RS_OneDay.php.

U.S. Naval Observatory
Astronomical Applications Department

Sun and Moon Data for One Day

The following information is provided for Spokane, Spokane County, Washington (longitude W117.4, latitude N47.7):

```
Wednesday
1 January 2014         Pacific Standard Time

                 SUN
Begin civil twilight       7:02 a.m.
Sunrise                    7:38 a.m.
Sun transit               11:53 a.m.
Sunset                     4:09 p.m.
End civil twilight         4:45 p.m.

                 MOON
Moonset                    3:53 p.m. on preceding day
Moonrise                   7:27 a.m.
Moon transit              12:14 p.m.
Moonset                    5:06 p.m.
Moonrise                   8:14 a.m. on following day
```

New Moon on 1 January 2014 at 3:15 a.m. Pacific Standard Time.

Figure 40. Complete sun and moon data for a day in a city. Retrieved from the United States Naval Observatory website: http://aa.usno.navy.mil/data/docs/RS_OneDay.php.

A categorical variable was then developed from information retrieved from the States Naval Observatory website (United States Naval Observatory, 2012). This variable represented information on whether burglaries occurred in daytime, nighttime, or extended/unknown hours. The following assumptions were made regarding timing of burglaries:

- Residential burglaries that took place in one day between begin and end of civil twilight were coded as daytime burglaries.
- Burglaries that occurred after end of civil twilight were coded as nighttime burglaries.
- Burglaries that occurred over an extended period of period of time (i.e. morning and evening hours, or involving several days) were coded as extended time burglaries. These burglaries are also known as burglaries that occur in unknown hours.

3.5.2.4 Security

One of the physical informational elements of crime reports is security. Even though crime reports should have information on security measures of burglarized premises and security is a measure which can be related to spatial characteristics of crime sites, this element was left out from analysis because of the following reasons:

- Around 50 percent of reports had no information on security.
- While in some occasions detailed phrases like lighting in yard, deadbolt, etc. were transcribed as descriptions for security, in some other instances, phrases like secured/non-secured were used for conveying information on security. Therefore, a secured premise might have lighting in yard, deadbolt lock on a door, or a combination of security measures without necessarily transcribing which security measures were available.
- In addition, since a clear definition for security was not available, premises may have security measures that were not observed or inquired by officers, and thereby not transcribed.

3.5.2.5 Type of premise

Another informational element of crime reports is type of burglarized premises. Similar to security, most crime reports did not have information on this variable. Thus, instead of utilizing information on type of premises from crime reports, I made a decision to use information on building use from building footprint shapefile available in the GIS & Simulation Lab at the Washington State University.

3.5.2.6 Method of entry

Another factor understood to be valuable for burglary studies is method of entry. This element shows information on whether burglaries were a forcible entry or not, what type of force was utilized for gaining entry into burglarized properties, and whether forcible or non-forcible entries were made by known individuals or known individuals. This element was not directly utilized in this study but taken into consideration along with demographics of victims to make decisions whether to include or exclude cases for analysis (See heading 3.5.2.8 for a discussion on which cases were included and excluded from analysis).

3.5.2.7 Demographic characteristics of victims

Lastly, I recorded information on age, sex and race of victims. Similar to method of entry, information on demographic characteristics of victims had informational purposes only and was not further processed. I made a decision not to include socio-economic characteristics of victims in statistical analysis to concentrate the study on physical characteristics of crime sites.

3.5.2.8 Summary

I studied 126 residential burglary crime reports for a 5-year period from January 1, 2006 through December 31, 2010 in the study area. I further processed informational elements of burglaries and stored them in an excel spreadsheet (See *Figure 41*). This excel spread sheet has information on: (1) year, (2) address, zip code, city and state, (3) type of entry points, (4) side (police_side), (5) day, (6) time, (7) week, (8) building identifier (Bldg_ID) and (9) building opening identifier (Target_ID) for burglaries.

Firstly, the year in which burglaries occurred were taken into account. Secondly, location of incidents including zip code, city and state was inscribed. Thirdly, type of entry points was dichotomized into a door or a window. Fourthly, side of buildings (i.e. front, back or side) on which building openings were located were transcribed. Fifthly, day of the week in which burglaries took place were taken into account. Sixthly, timing of burglaries was measured (i.e. daylight, darkness or extended/unknown hours). Next, it was transcribed whether burglaries occurred in weekdays, weekends or extended/unknown time frames involving weekday and weekdays. Lastly, unique identifies developed for building openings and buildings were used to associate crime and spatial data.

Number	Year	Address	Zip Code	City	State	Type of entry points	Police_Side	Day	Time	Week	Bldg_ID	Target_ID
1	2010	[redacted]				Door	Front	Tuesday	Darkness	Weekday	[redacted]	
2	2009	[redacted]				Door	Back	Extended	Extended	Weekday	[redacted]	
3	2008	[redacted]				Window	Side	Sunday	Daylight	Weekday	[redacted]	
4	2007	[redacted]				Door	Front	Wednesday	Daylight	Weekend	[redacted]	
5	2006	[redacted]				Door	Back	Saturday	Darkness	Weekend	[redacted]	

Figure 41. Crime data (Source: Author).

Reviewing crime reports, I first decided to only include cases representing characteristics of a general residential burglary. Attempted burglaries at residential establishments were also taken into consideration if building openings were approached for breaking and entering purposes. However, cases in which victimization were made by a known-individual were excluded. In addition, cases involving gang, robbery, malicious mischief or assault activities were left out. These cases were excluded because victims and suspects known each other or victimized properties from the past, and victimization occurred not solely for burglarizing purposes.

Taking into account the above mentioned criteria, I was only able to prepare 72 cases for geocoding even though 126 burglary crime reports were read. To ameliorate the low case to variable ratio (dependent-independent variable ratio) and increase the number of cases for analysis, I and my committee member from the department of criminology read my notes on burglary reports one by one and made decisions regarding inclusion or exclusion of each case for further processing and analysis. I was able to prepare 120 cases for geocoding after second reviewal of crime data. Six cases were excluded or merged because they were either one incident recorded as two, committed inside of buildings (i.e. breaking and entering into another room) or did not involve unlawful entry to a building.

3.5.3 Geocoding crime data

I used parcel geocoder and google maps address finder for geocoding crime data. Spokane County parcel geocoder, available in the Washington State University GIS & Simulation Lab database, was used for geocoding address of burglarized dwellings. I also utilized google maps to locate address of burglarized buildings and to make sure that addresses are precisely geocoded. Out of 120 cases prepared for geocoding, I was able to geocode and prepare 118 burglaries for further analysis because of the following reasons;

- One address could not be located by the geocoder. I walked in that street segment and adjacent street blocks trying to locate that address through a site survey visit, nevertheless efforts were not successful.

- No building existed in one of the geocoded parcels. According to the building footprint shapefile as of year and 2004 and a 6 inch color aerial imagery covering the Spokane metro area captured in year 2007 (City of Spokane, 2013), I believe this building was demolished sometime between 2004 and 2007.

After completion of the geocoding procedure, unique identifies developed for building openings and buildings were used to link crime and spatial data. The following sections provide chi-square or descriptive statistics on characteristics of residential burglaries at the building opening and building level (Refer to Appendix D for further chi-square statistics).

3.5.3.1 Targeted building openings

I was able to geocode118 residential burglaries between 2006 and 2010 in the study area. From 118 burglary commissions, 91 occurred in the area in which measures of surveillability were developed for building openings (See *Figure 52*). Further, out of the 91 burglary commissions, 70 (76.92%) had known entry points, 13 entry points (14.29%) were inaccurately transcribed, 4 (4.40%) had unknown entries and 4 (4.40%) were not geocoded[22] (See Table 28). From the 70 known burglary commissions, three building openings were targeted multiple times. I counted multiple victimized entry points once (because of statistical techniques utilized in this study) and had 65 burglary commissions at the building opening level.

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[22] Pictometry oblique aerial imagery does not provide adequate information on basement windows because they are small to be observed and/or covered by vegetation. Thus, windows to basements could not be georeferenced. However, windows to residences in basement floors could be georeferenced because of their size and availability of some other building features like stairs leading to basements.

Table 28

Frequency of burglary commissions in a 5-year period between 2006 and 2010 in the study area (Source: Author).

Entry Points	Frequency	Percent
Known	70	76.92
Inaccurate	13	14.29
Unknown	4	4.40
Not Geocoded	4	4.40
Total	91	100.00

46 (70.80%) burglary commissions occurred through a door, and 19 (29.20%) happened through a window (See Table 29). The results of chi-square statistics indicated a statistically significant difference between opening type (i.e. door vs. window) and burglary commission ($\chi^2 = 103.80$, df = 1, $p < 0.001$). More doors than expected and fewer windows than anticipated were used for burglary commission. The odds of burglary commission through doors was 10 times greater than burglary commission through windows (OR = 10.10, 95% CI = 5.88-17.37). Further, the risk of burglary commission through doors was 9 times more likely than burglary commission through windows (RR = 9.46, 95% CI = 5.58-16.03).

Table 29

The relationship between opening type and burglary commissions (Source: Author).

		Offence		
Opening Type		Burglarized	Non-burglarized	Total
Door	f	46	602	648
	%	1.40%	18.90%	20.40%
Window	f	19	2512	2531
	%	0.60%	79.00%	79.60%
Total	f	65	3114	3179
	%	2.00%	98.00%	100%

Out of 65 burglary commissions, 46 (70.80%) occurred through a door, whereas 19 (29.20%) happened through a window. Out of 46 (70.80%) through door burglary commissions, 28 (43.10%) are located in front of dwellings while 18 (27.70%) are situated in rear side of residences. In addition, out of 19 (29.20%) through window burglary commissions, 6 (9.20%) are placed in front, 8 (12.30%) are located in rear and 5 (7.70%) are situated in side of residential dwellings. The results of chi-square statistics indicated a statistically significant difference between type and side of targeted building openings ($\chi2 = 14.34$, df = 2, Fisher's exact $p = 0.001$). According to crosstab statistics, most burglary commissions were committed through front door followed by back door and back window (See *Figure 42*).

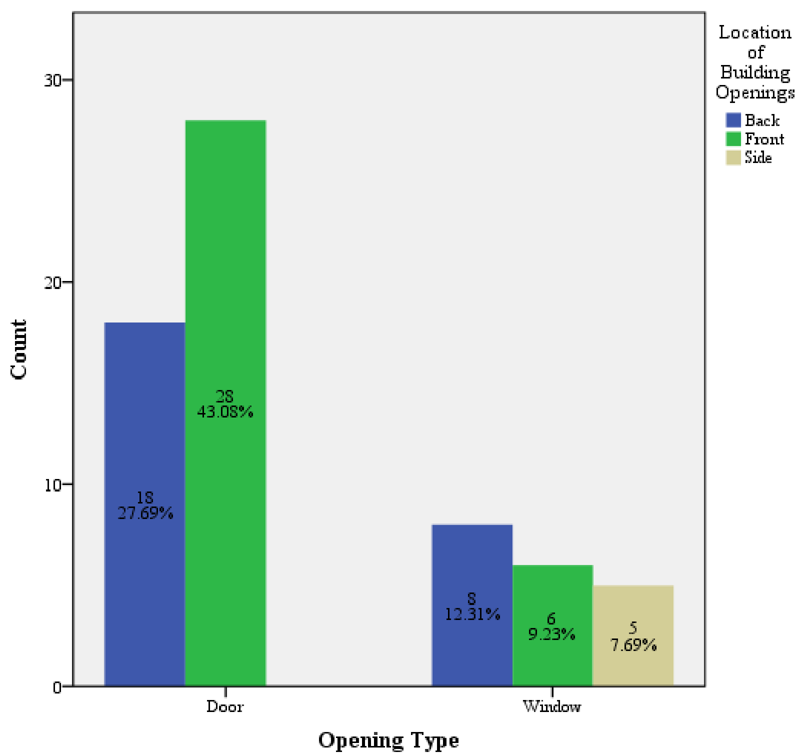


Figure 42. Placement of targeted building openings (Source: Author).

Taking into consideration the estimated range of time of offence, out of 65 burglary commissions, 28 (43.10%) occurred in daylight hours, 15 (23.10%) took place in darkness and

22 happened (33.80%) in extended/unknown hours. Further, out of 46 (70.80%) through door committed burglaries, 22 (33.80%) doors were approached in daylight, 8 (12.30%) in darkness and 16 (24.60%) in extended/unknown hours. In addition, out of 19 (29.20%) through window burglary commissions, 6 (9.20%) windows were approached in daylight, 7 (10.80%) in darkness and 6 (9.20%) in extended/unknown hours. The results of chi-square statistics demonstrates an insignificant relationship between type of targeted building openings and the estimated range of time of offence ($\chi2 = 3.07$, df = 2, Fisher's exact $p > 0.05$). Even though this relationship was statistically insignificant, burglary commission through doors during daylight hours was the most common breaking and entering pattern (See *Figure 43*).

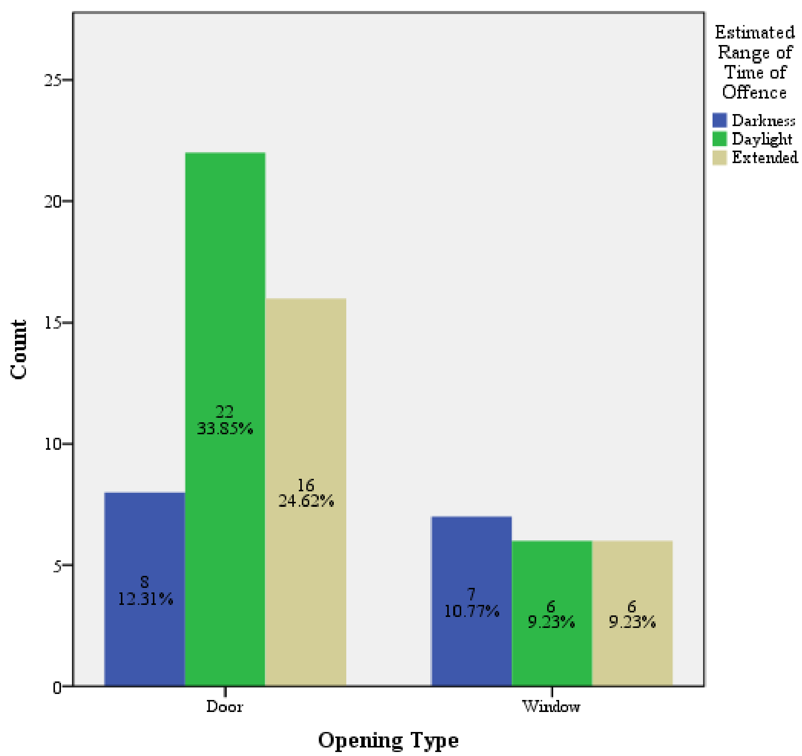


Figure 43. Estimated range of time of offence of burglary commissions (Source: Author).

Taking into account another measure of time, out of 65 burglary commissions, 37 (56.90%) occurred in weekdays, 18 (27.70%) during weekends and 10 (15.40%) in extended/unknown hours (involving weekday and weekdays). Out of 46 (70.80%) through door committed burglaries, 22 (33.80%) were targeted in weekdays, 15 (23.10%) in weekends and 9 (13.80%) in extended/unknown time periods. In addition, out of 19 (29.20%) through window committed burglaries, 15 (23.10%) were targeted in weekdays, 3 (4.60%) in weekends and 1 (1.5%) in extended/unknown hours. The results of chi-square statistics demonstrated an insignificant relationship between type of targeted building openings and time of offence (χ^2 = 5.45, df = 1, Fisher's exact $p > 0.05$). Even though this relationship was statistically insignificant, most burglary commissions occurred in weekdays (See *Figure 44*).

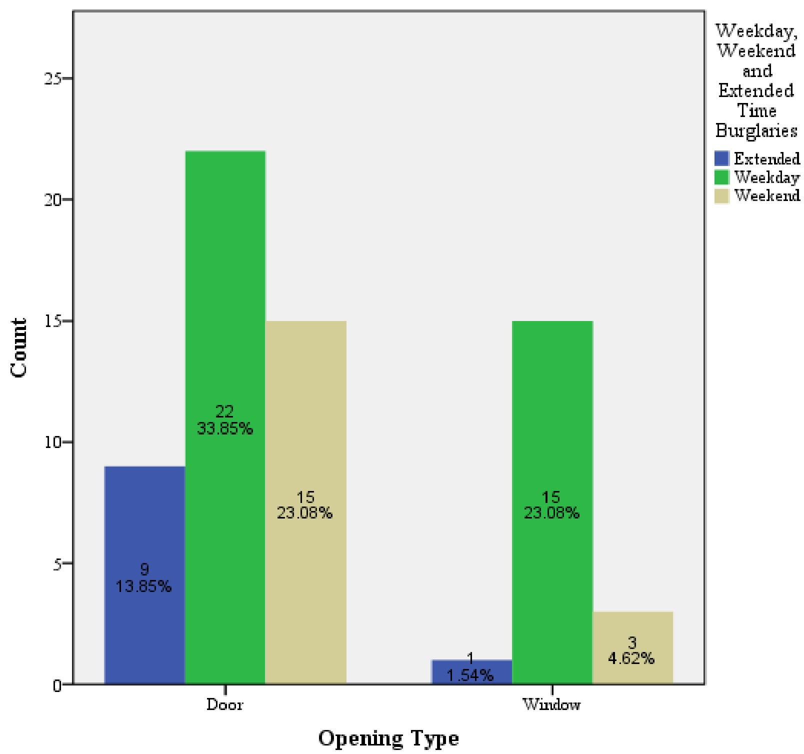


Figure 44. Weekday, weekend and extended/unknown burglary commissions (Source: Author).

3.5.3.2 Targeted buildings

The 118 geocoded burglary commissions took place in 83 residential dwellings. From 83 burglary commissions, 62 occurred in the area in which measures of surveillability were developed for buildings (See *Figure 53*). Thus, in a 5-year period between 2006 and 2010, 62 residential burglaries joined to spatial data at the building level.

Taking into consideration the estimated range of time of offence, out of 62 burglaries, 19 (30.60%) occurred in daylight hours, 10 (16.10%) took place in darkness and 33 happened (53.20%) in extended/unknown hours (See Figure 45).

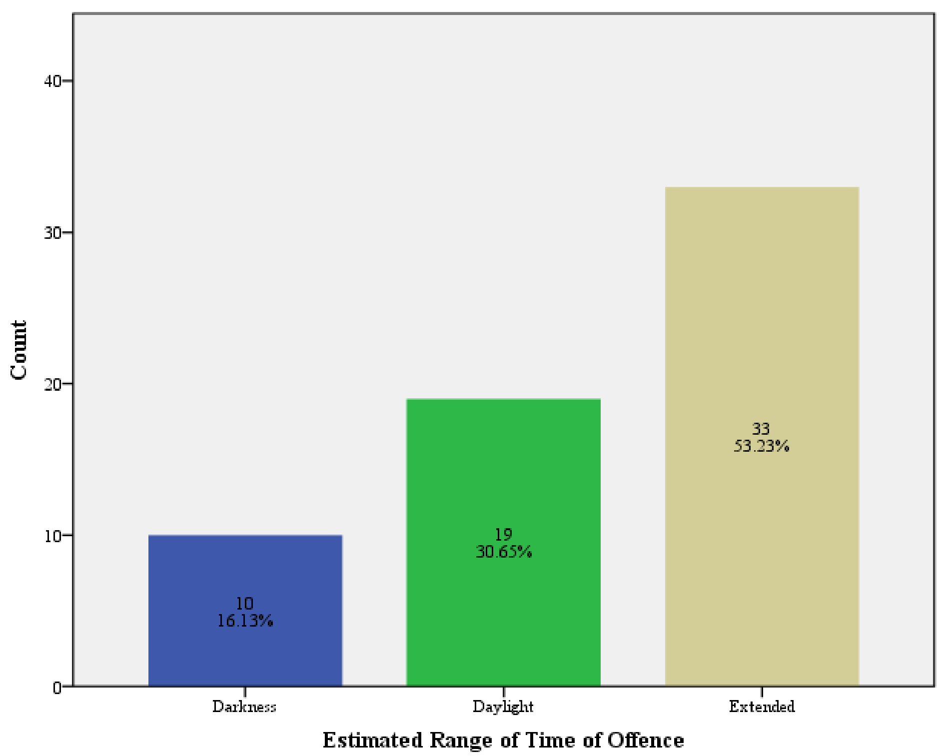


Figure 45. Estimates range of time of residential burglaries (Source: Author).

Taking into account another measure of time, out of 62 burglaries, 31 (50.00%) occurred in weekdays, 13 (21.00%) during weekends and 18 (29.00%) in extended/unknown (involving weekday and weekdays) time periods (See Figure 46).

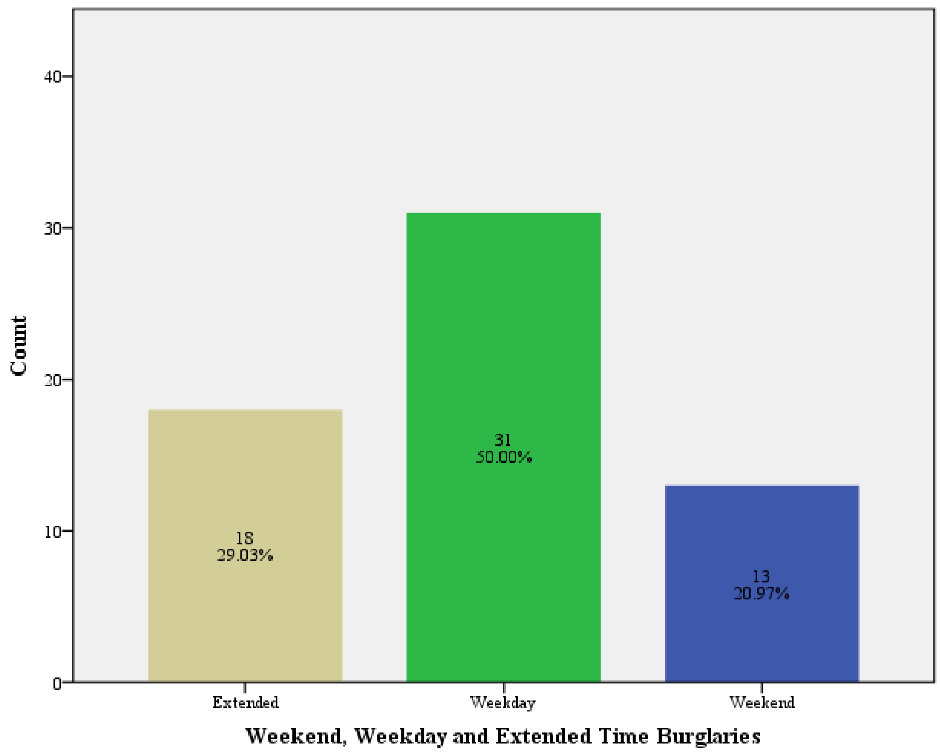


Figure 46. Weekday, weekend and extended/unknown time burglaries (Source: Author).

3.6 Variables

This section is comprised of three parts and elaborates on dependent, interdependent and control variables. Independent variables are comprised of occupant, road and pedestrian surveillability data. Burglary crime data constitute dependent variable. Covariates are comprised of theoretically important variables such as building use, territoriality, diversity (availability of non-residential facilities in residential neighborhoods), maintenance, vacant lot, corner/middle lot, no-trespassing symbols and facing of building openings or buildings (to different types of roads or buildings).

3.6.1 Dependent variables

The dependent variable called "offence_141" is a dichotomous variable showing information on burglarized building openings at the building opening level or burglarized buildings at the building level. Prior to analysis the variable offence_141 was recoded in SPSS as dichotomous with 0 = not burglarized and 1 = burglarized. I geocoded 65 burglary commissions at the building opening level, and 62 residential burglaries at the building level in the area in which measures of visibility were developed for buildings openings and buildings (See *Figure 47*).

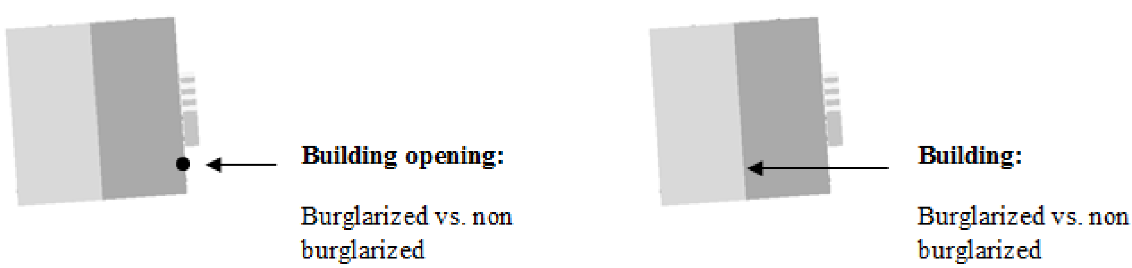


Figure 47. Dependent variables at the building opening and building level (Source: Author).

3.6.2 Independent variables

Independent variables are comprised of the surveillability data. At the building opening level, there are 9 independent variables; 3 quantifying occupant surveillability (Oc49_BVBL, Oc95_BVBL and Oc141_BVBL), 3 representing road surveillability (Rd49_BVBL, Rd95_BVBL and Rd141_BVBL) and 3 showing pedestrian surveillability (Sw49_BVBL, Sw95_BVBL and Sw141_BVBL) within three distances of 49, 95 and 141 feet of building openings. At the building opening level, the number of visible sightlines to building openings, to road centerline points and to street centerline points constituted the independent variables (See *Figure 48*).

At the building level, I aggregated the number of sightlines that survey a building from building openings, road centerline points and street centerline points. I then developed 9 surveillability measures; 3 quantifying occupant surveillability (SUM_OC49_BVBL, SUM_OC95_BVBL and SUM_OC141_BVBL), 3 representing road surveillability (SUM_RD49_BVBL, SUM_RD95_BVBL and SUM_RD141_BVBL) and 3 showing pedestrian surveillability (SUM_SW49_BVBL, SUM_SW95_BVBL and SUM_SW141_BVBL) within three distances of 49, 95 and 141 feet of buildings (See *Figure 48*).

Building openings:

Independent variables are comprised of number of visible sightlines to a building opening.

For instance 2 sightlines survey a building opening.

Buildings:

Independent variables are comprised of sum total number of visible sightlines to a building.

For instance 4 sightlines survey a building.

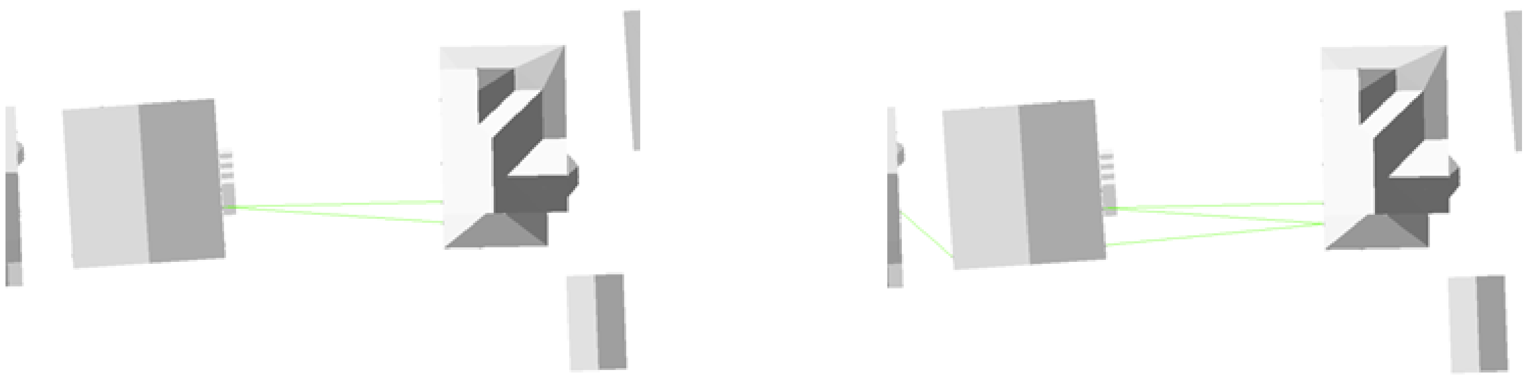


Figure 48. Independent variables at the building opening and building level for occupant surveillability (Source: Author).

3.6.3 Control variables

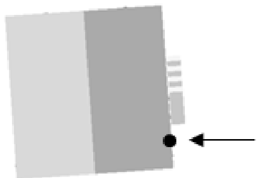
Control variables are comprised of theoretically important variables. At the building opening level, eight theoretically important variables (building use, territoriality, diversity, maintenance, vacant lot, corner/middle lot, no-trespassing symbols and facing of building openings) were utilized. At the building level, seven control variables (building use, diversity, maintenance, vacant lot, corner/middle lot, no-trespassing symbols and facing of buildings) were used.

Description of some variables such as building use, maintenance, adjacent vacant lot, corner/middle lot and availability of no-trespassing symbols are consistent at the building opening and building level. Building openings have characteristics of buildings they belong to. Building use is categorized into classes of one-family dwellings and multi-family dwellings (Bldg_Use_Type). Premises are divided into maintained or non-maintained properties (Maintenance). Dwellings adjacent to vacant lots are separately coded (Adjacent_Vacant). Corner and middle lot dwellings are differentiated (CornerMiddle_Lots). Premises with no-trespassing or warning signs are distinguished (Trespass_Sign).

Some other variables such as diversity and facing of buildings are defined differently, when recorded at the building opening and building level. Diversity at the building opening level is defined as availability of non-residential facilities within 49, 95 and 141 feet of building openings (Facilities_49, Facilities_95 and Facilities_141). At the building level, dwellings that have at least one building opening in proximity to non-residential facilities are coded as buildings within 49, 95 and 141 feet proximity to non-residential facilities (FACILITIES_49, FACILITIES_95 and FACILITIES_141).

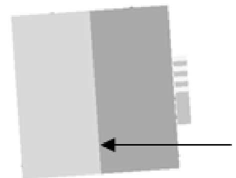
In regard to facing of building openings and buildings, buildings openings either face an alley, a regional street, a neighborhood collector or another building (Opening_Face). At the building level, buildings either face a regional street or a neighborhood collector (Bldg_Face).

Lastly, taking into account territoriality, building openings that were clearly demarcated by public space by see-through or solid facing are considered completely demarcated openings, otherwise they are considered accessible to the public (Territory). This variable was not computed at the building level because perimeter of most buildings was not completely demarcated from the public space.



Building openings:

1. Building use
   a. 1 unit
   b. 2 plus units
2. Diversity
   a. Presence of non-residential facilities within 49, 95 and 141 feet
   b. Absence of non-residential facilities within 49, 95 and 141 feet
3. Maintenance
   a. Maintained
   b. Not maintained
4. Vacant lot
   a. Adjacent vacant lot
   b. Adjacent built
5. Corner vs. middle lot
   a. Corner lot
   b. Middle lot
6. No-trespassing symbols
   a. Noticeable
   b. Not available
7. Territoriality
   a. Completely fenced
   b. Accessible to public
8. Facing
   a. Alley
   b. Regional street
   c. Neighborhood collector
   d. Building



Buildings:

1. Building use
   a. 1 unit
   b. 2 plus units
2. Diversity
   a. Presence of non-residential facilities within 49, 95 and 141 feet
   b. Absence of non-residential facilities within 49, 95 and 141 feet
3. Maintenance
   a. Maintained
   b. Not maintained
4. Vacant lot
   a. Adjacent vacant lot
   b. Adjacent built
5. Corner vs. middle lot
   a. Corner lot
   b. Middle lot
6. No-trespassing symbols
   a. Noticeable
   b. Not available
7. Facing
   a. Regional street
   b. Neighborhood collector

Figure 49. Control variables at the building opening and building level (Source: Author).

3.7 Analyzing and categorizing natural surveillance

Previous crime pattern studies have grounded analysis or quantification of natural surveillance on street segment, street block or block-face (Brown & Altman, 1983; Hillier, 2004; Weisburd et al., 2012). However, I believe that street segment should not be considered an appropriate unit for natural surveillance-crime studies. The rationale for this proposition is based on the following grounds:

- The unit of analysis should be universal applicable to any context regardless of diverse planning and design approaches and policies.
- Urban grid or other network systems vary in rural, urban and suburban environments.
- Length and shape of blocks (and accordingly street segments) vary in different network systems making it hard in many spatial configurations to objectively decide which parcel or building should belong to which street segment (See *Figure 50*).
- Any proposed unit of analysis should be 3-dimensional (and not 2-dimensional).
- Lastly, the range human eye can see in a given direction is an important part of natural surveillance; therefore, considerations should be made regarding the distance at which human eye can be effective for observing and interpreting a witnessed incident.

Figure 50. Unit of analysis in street segments or blocks. Left: This block may be considered the most perfect form of a long block facing two smaller blocks. The longer street segment can be easily split into two and decisions can be made regarding which houses belong to which street segments. Right: In these blocks it would be hard to objectively decide where the unit of analysis starts and where it end, and to which street segment some houses belong to (Source: Author).

Eyewitness identification literature helped me develop a sophisticated methodology for analysis of natural surveillance. According to Lindsay et al. (2008), the most reliable distance for face recognition takes place within 49 feet distance from an eyewitness. In addition, some value or accuracy can be found in judgments within 141 feet distance of eyewitness individuals. Thus, I quantified natural surveillance at the following distances (See *Figure 51*):

1. 49 feet (15 meters) representing the most reliable distance for face recognition purposes.
2. 95 feet (29 meters) representing the mean distance between the most reliable distance and still dependable distance for spectating;
3. 141 feet (43 meters) representing a distance with some value or accuracy for eyewitnessing.

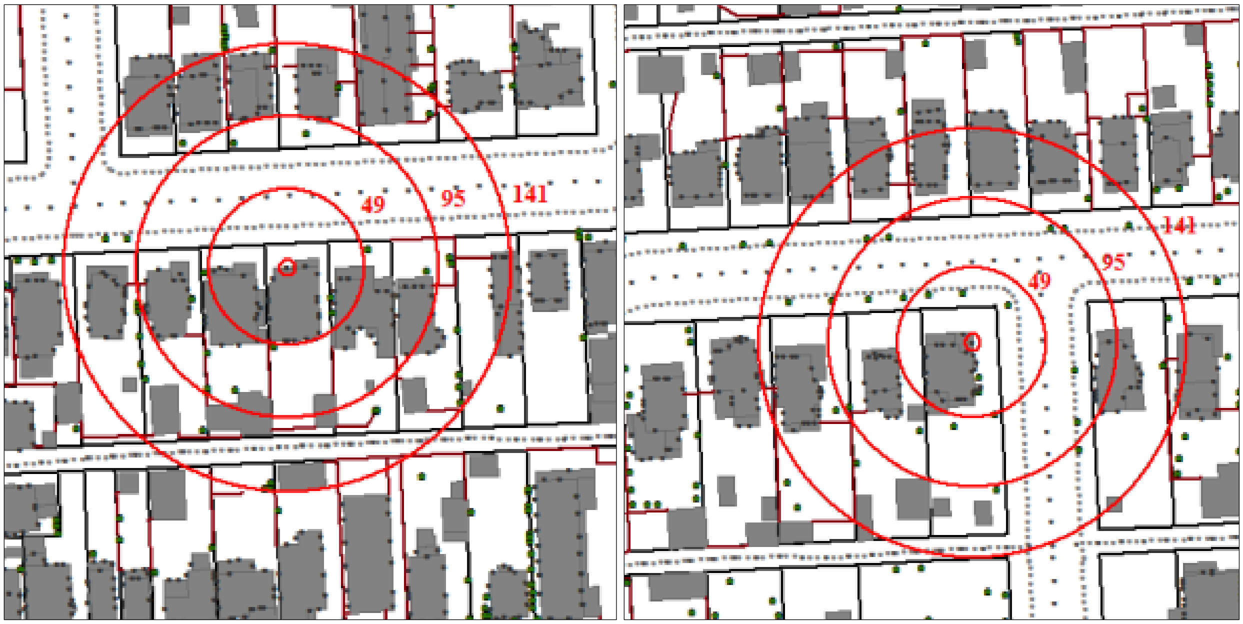


Figure 51. Areas within 49, 95 and 141 feet around building openings (Source: Author).

To determine which building openings and buildings are located within the farthest surveillability distance of houses adjacent to the study area, a polygon was drawn on edges of buildings overlooking the block group study area. This polygon was exported to AutoCAD, offset 141 feet inward and imported back to ArcMap. Only points located within the offset polygon can be considered as target points because observer points within 141 feet of these points are georeferenced (See *Figure 52*). In addition, buildings that are completely within the offset polygon can be considered potential targets (See *Figure 53*).

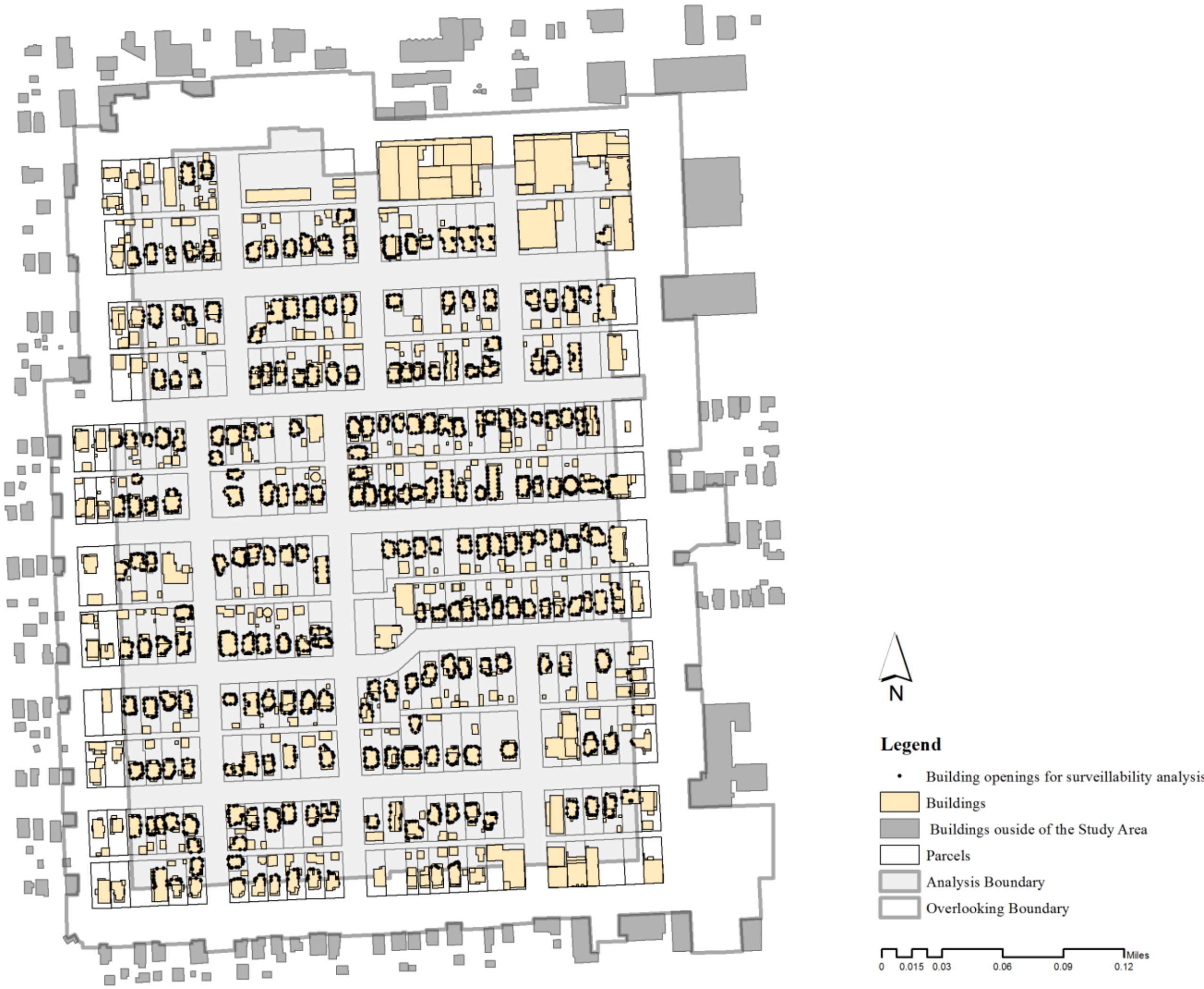


Figure 52. Building openings inside the surveillability analysis boundary (Source: Author).

Figure 53. Buildings inside the surveillability analysis boundary (Source: Author).

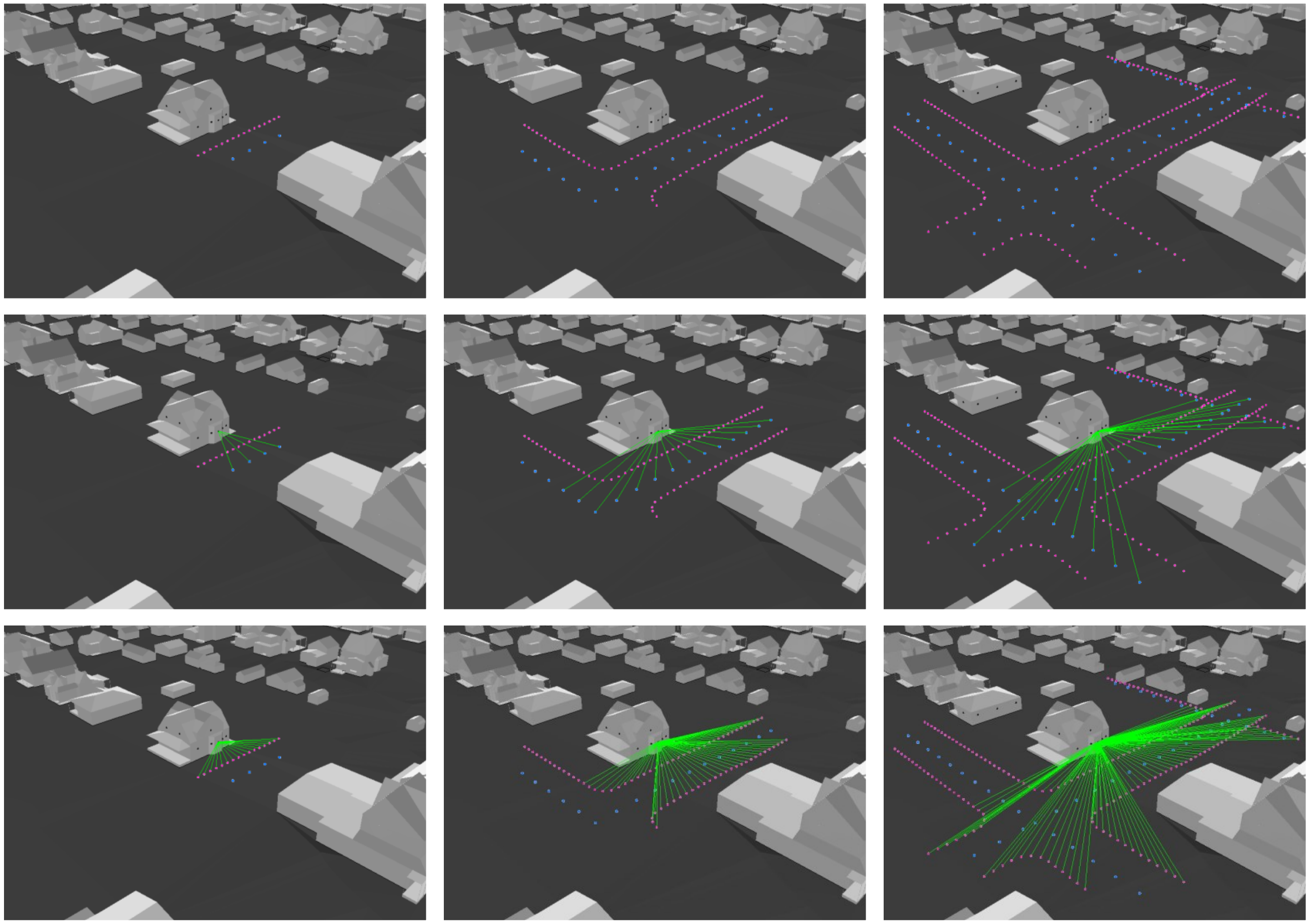
3.8 Measures of natural surveillance

Former studies have categorized natural surveillance into two categories of occupant surveillability and road surveillability (Brown & Altman, 1981; Ham-Rowbottom et al., 1999; Macdonald & Gifford, 1989; K. T. Shaw & Gifford, 1994). I introduced a third measure called pedestrian surveillability to the above mentioned measures of surveillability. Even though road and pedestrian surveillability may seem similar at the first sight, the eye height of human beings and the corresponding surveillance ability are different in the sitting and standing position. Thus, I quantified surveillability as seen by neighbors (occupant surveillability), from cars on roads (road surveillability) and by pedestrians on curblines (pedestrian surveillability). Surveillability categories are defined in the followings:

- Occupant surveillability quantified surveillability of building openings and buildings as seen by neighbors. I generated sightlines from building openings to all other building opening to residential dwellings.
- Road surveillability quantified surveillability of building openings and buildings from points placed on road centerlines. I generated sightlines from building openings to circumscribing road points.
- Pedestrian surveillability quantified surveillability of building openings and buildings from points placed on curblines. I generated sightlines from building openings to circumscribing curbline points.

I computed surveillability for each of the above mentioned categories at three distance measure of 49 feet, 95 feet and 141 feet. Therefore, my analysis was comprised of 3 categories of surveillability and 3 distance measures (See *Figure 54*).

49 feet 95 feet 141 feet



Occupant Surveillability

Road Surveillability

Pedestrian Surveillability

Figure 54. Occupant, road and pedestrian surveillability (Source: Author).

3.8.1 Variations in natural surveillance

Each cell in my 3x3 table of surveillability was comprised of eight scenarios, each having one sub-scenario. I developed these scenarios to help understand the role that each individual (buildings, street vegetation, yard vegetation and visual barriers) or combinations of variables might play in variations of surveillability in each category and distance. The base scenario quantifies the number of visible sightlines to building openings taking into account length of 3-dimensional sightlines in 2-dimensions. The sub-scenario enumerates the number of visible sightlines after computing the 3-dimentions length of visible sightlines and restricting lengths by the corresponding surveillability distance measure Scenarios are discussed below and shown in Table 30:

- Scenario 1 solely has buildings for analysis of surveillability.
- Scenario 2 had buildings and visual barriers for analysis of surveillability.
- Scenario 3 included buildings and street vegetation for analysis of surveillability.
- Scenario 4 is comprised of buildings and yard vegetation for analysis of surveillability.
- Scenario 5 included buildings, yard vegetation and street vegetation for analysis of surveillability.
- Scenario 6 is comprised of buildings, street vegetation and visual barriers for analysis of surveillability.
- Scenario 7 consisted of an environment with buildings, yard vegetation and visual barriers for analysis of surveillability.
- Scenario 8 consisted of buildings, yard vegetation, street vegetation and visual barriers for analysis of surveillability.

Table 30

Variations of natural surveillance according to individual or combinations of architectural and landscape features (Source: Author).

Scenarios		3D Multipatch Features (+ Human Vision Capability)
1	a, b	Buildings (+ Myopic Distance)
2	a, b	Buildings + Visual Barriers (+ Myopic Distance)
3	a, b	Buildings + Street Vegetation (+ Myopic Distance)
4	a, b	Buildings + Yard Vegetation (+ Myopic Distance)
5	a, b	Buildings + Yard Vegetation + Street Vegetation (+ Myopic Distance)
6	a, b	Buildings + Street Vegetation + Visual Barriers (+ Myopic Distance)
7	a, b	Buildings + Yard Vegetation + Visual Barriers (+ Myopic Distance)
8	a, b	Buildings + Yard Vegetation + Street Vegetation + Visual Barriers (+ Myopic Distance)

3.9 Summary

I utilized georeferenced data and geospatial technologies to analyze spatial and crime data in an area in Spokane, Washington. I then introduced and developed a new methodology for analyzing natural surveillance based on eyewitness identification distance and according to whether observation takes place by neighbors, passersby on foot or individuals in vehicles. Lastly, I proposed to study and quantify the role that each individual or combinations of architectural and landscape features plays in variations of surveillability.

4 SURVEILLABILITY MODELBUILDER

4.1 Introduction

This chapter concentrates on an application of geospatial technologies for automating the procedure of surveillability enumeration and quantification. Three visual programming tools were developed in the ESRI ArcGIS platform to quantify occupant, road and pedestrian surveillability in 3-dimentions. Tools utilized in addition to input and output feature classes or tables from each tool are also discussed in detail.

4.2 ESRI GIS ModelBuilder

ModelBuilder, a visual programming tool for creating workflows, is an application for creating, editing, running and managing tools in the ESRI ArcGIS platform (Esri, 2014a). Models like workflows consist of strings of geoprocessing tools over which the output of one tool is fed into another tool as input. Models are best to be utilized when a sequence of data and tools are to be chained together for a final output (Esri, 2014a).

I used ArcGIS ModelBuilder to automate the procedure of enumerating and quantifying occupant, road and pedestrian surveillability at three distance measures of 49, 95 and 141 feet. This way, I linked input data to tools or functions in ArcGIS and avoided manually going through the process of selecting databases and feeding the output of one tool into other tools. Models are discussed in the following sections.

4.3 The Occupant, Road and Pedestrian Surveillability ModelBuilder

The occupant, road and pedestrian surveillability models started with target points as the input feature class. This point feature class was fed into an iterator that looped over each individual target point and fed each selected point into the select layer by location tool, where observer points within a distance of a specified target point were selected. Sightlines were then constructed from observer points to that specified target, and visibility along sightlines was computed by the line of sight analysis tool. Output tables for this model showed the total number of possible and visible sightlines for each scenario (See *Figure 55* and *Figure 56*). Each surveillability ModelBuilder was run 3 times for each distance measure of surveillability. It took 5-7 days for each model to run on an Intel Quad Core i7 16 GB RAM desktop computer in the GIS & Simulation Lab.

Input features for the occupant, road and pedestrian surveillability models were comprised of observer points, target points and 3-dimensional Multipatch features. 3-dimensional observer points vary between surveillability models, while target points and 3-dimensional Multipatch features were consistent along the occupant, road and pedestrian surveillability models.

For the occupant surveillability model, observer points are comprised of 3-dimensional building openings to residential dwellings. I did not include building openings to non-residential facilities as observer points, but created a field and recorded building openings that within 49, 95 and 141 feet of non-residential facilities. For the road surveillability model, 3-dimensional points representing road centerlines constituted observer points. And for the pedestrian surveillability model, 3-dimensional points representing road centerlines were considered observers.

3-dimensional Multipatch features were comprised of 3-dimensional models of building, street vegetation, yard vegetation and visual barriers. Lastly, 3-dimensional target points were comprised of a subset of 3-dimensional building openings in the study area. The following assumptions were made for selecting target points (See Table 31):

- This study wishes to make predictions regarding commission of residential burglaries. Therefore, doors and windows to residential buildings constituted target points.
- Doors located on any floor in addition to windows on basement and first floors of residential buildings were considered approachable targets to burglars. The rationale for this selection can be explained in two respects; firstly, staircases provide access to doors on any floor of residential buildings and may be approached by all. Secondly, just basement and first floor windows are located at an accessible height for intruders. Burglars might not be willing to attract attention by carrying suspicious tools (i.e. ladders, etc.) or displaying suspicious behaviors (i.e. climbing trees) for break-in purposes.
- Analysis of surveillability in this study was grounded on three distance measures around building openings. The farthest distance for this analysis was 141 feet around building openings. Thus, I only included building openings in the offset polygon shown in *Figure 52* because observer points within 141 feet of these points were georeferenced.

Table 31

Tools utilized for selecting target points in the study area (Source: Author).

Tool	Parameters	
Select Layer By Attribute	Layer Name or Table View	Bldg_Opening
	Selection Type	NEW_SELECTION
	Expression	Bldg_Use = 'Residential'
Select Layer By Attribute	Layer Name or Table View	Bldg_Opening
	Selection Type	SUBSET_SELECTION
	Expression	ID_Opening LIKE '_____0W__' OR ID_Opening LIKE '_____1W__' OR ID_Opening LIKE '______D__'
Select Layer By Location	Input Feature Layer	Bldg_Opening
	Relationship	COMPLETELY_WITHIN
	Selecting Features	Boundary_Analysis_CAD
	Selecting Type	SUBSET_SELECTION
Add Field	Input Table	Bldg_Opening
	Field Name	Target_141
	Field Type	Text
Calculate Field	Input Table	Bldg_Opening
	Field Name	Target_141
	Expression	Target_141 = “Yes”

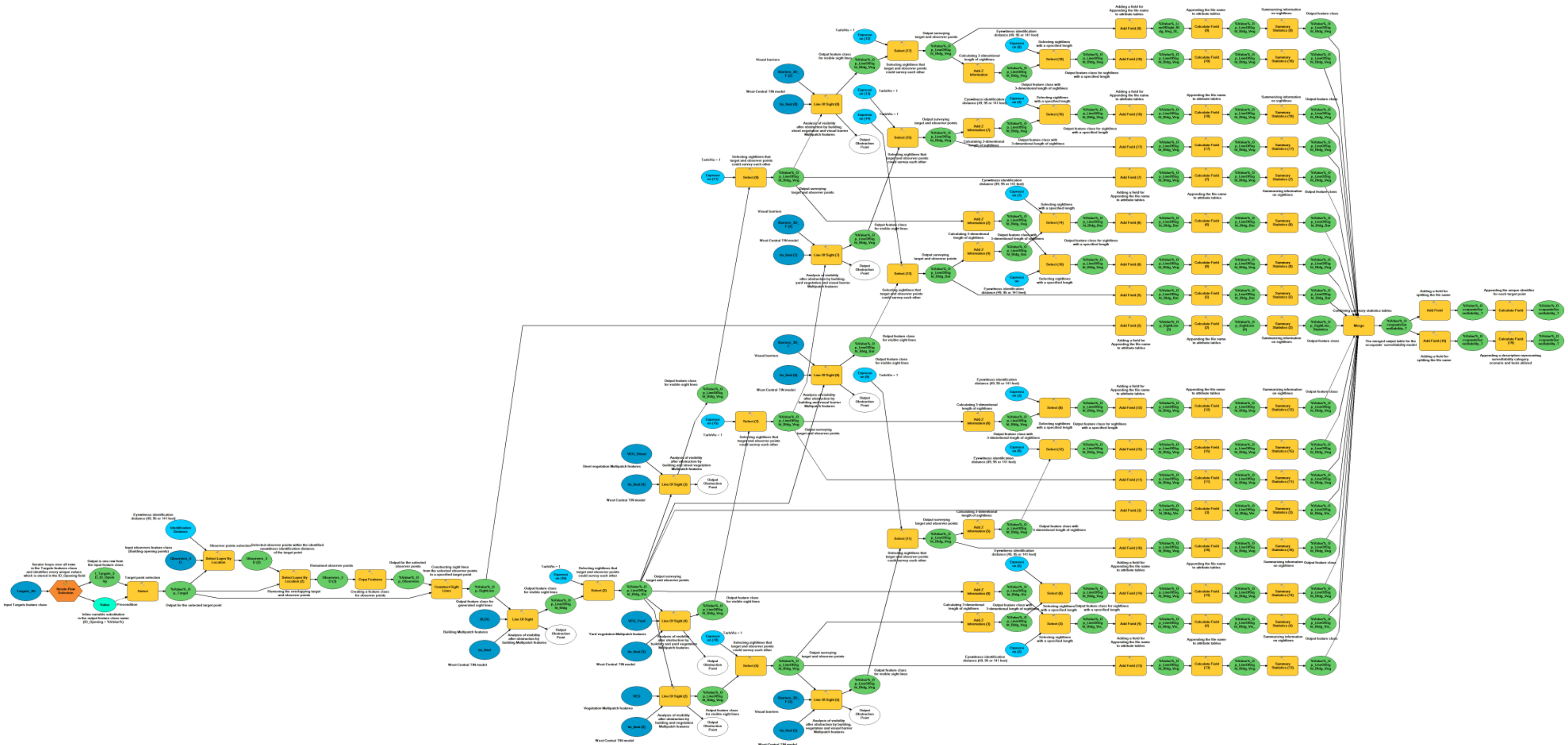


Figure 55. The occupant surveillability model (Source: Author).

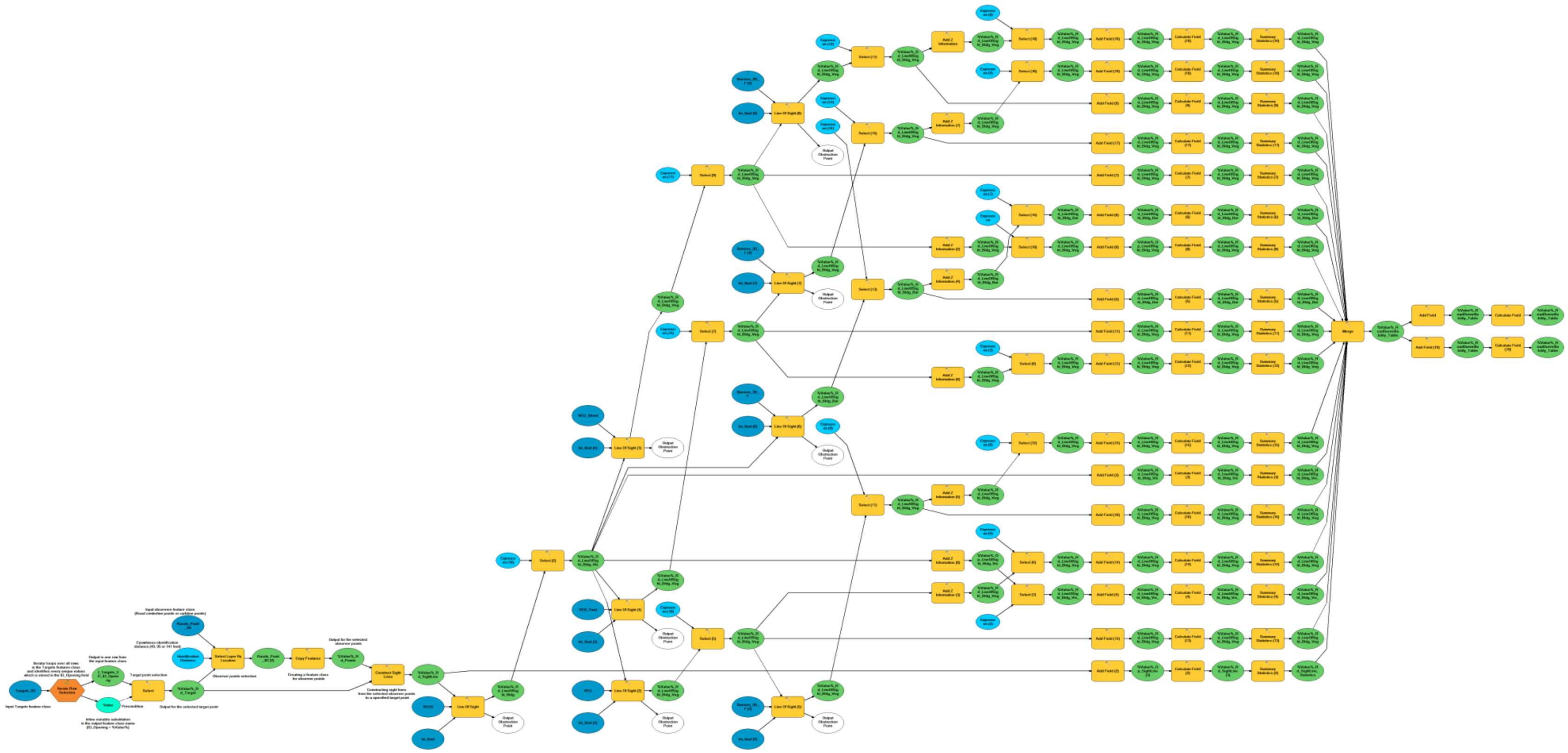


Figure 56. The road and pedestrian surveillability models (Source: Author).

4.3.1 The Occupant Surveillability

The occupant surveillability model computed surveillability of building openings as seen by neighboring building openings to residential dwellings. The input feature classes for this model were comprised of 3-dimensional target points, 3-dimensional observer points representing building openings to residential dwellings and 3-dimensional Multipatch feature representing architectural and landscape features on the surface of the earth. The procedure for computing occupant surveillability is elaborated in the following paragraphs.

4.3.1.1 Iteration, selection and inline variables

The occupant surveillability model began with a target point feature class. This point feature class was fed into a row iterator that looped sequentially through a table of all points and selected one record. This selection was made based on the “ID_Opening” field (the unique identifier developed for building openings). Two outputs were generated for each selected feature; the output selected row and the value of the selected row (here the “ID_Opening” value). The output selected row was then fed into the select tool to create a point feature class for each output selected row. The value field representing the unique identifier for the selected building opening was set as precondition for the select tool. This way, the unique identifier for the target building openings were used as inline variable (%Value%) in subsequent tools. Using inline variable substitution, the unique identifier for each specified target point was added to the output name of subsequently utilized tools (See Table 32 and *Figure 57*).

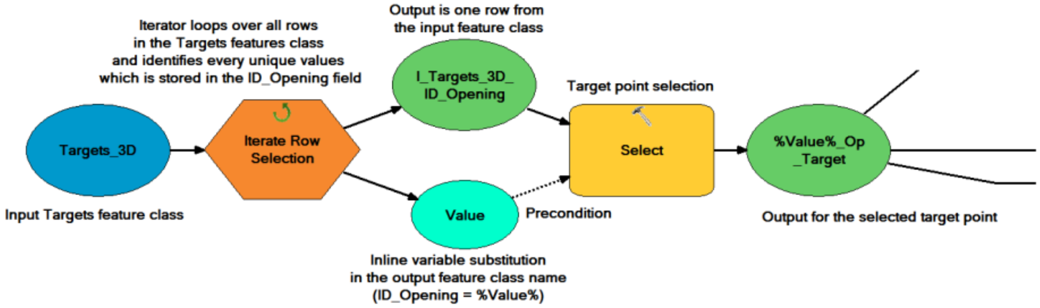


Figure 57. Chain of iteration and inline variable substitution in the occupant surveillability model (Source: Author).

Table 32

Tools utilized for iteration and inline variable substitution in the occupant surveillability model (Source: Author).

Tool	Parameters	
Iterate Row Selection	Input Table	Targets_3D
	Group by Fields	ID_Opening
Select	Input Features	I_Targets_3D_ID_Opening
	Output Feature Class	%Value%_Op_Target

Next, each selected target point was fed into the select layer by location tool where observer points within a distance (49, 95 or 141 feet in each run of the model) of a selected target were selected. The observer feature class consisted of all building openings to residential dwellings in the study area, resulting in a selected target to be included as a potential observer. This duplication was removed by setting a spatial relationship in the select layer by location tool. Defining an intersecting relationship, any point (here one point) overlapping with a selected target point was removed. After exclusion, this subset selection encompassing observer points within a distance of a selected target point were exported as a feature class by the copy features tool (See Table 33 and *Figure 58*).

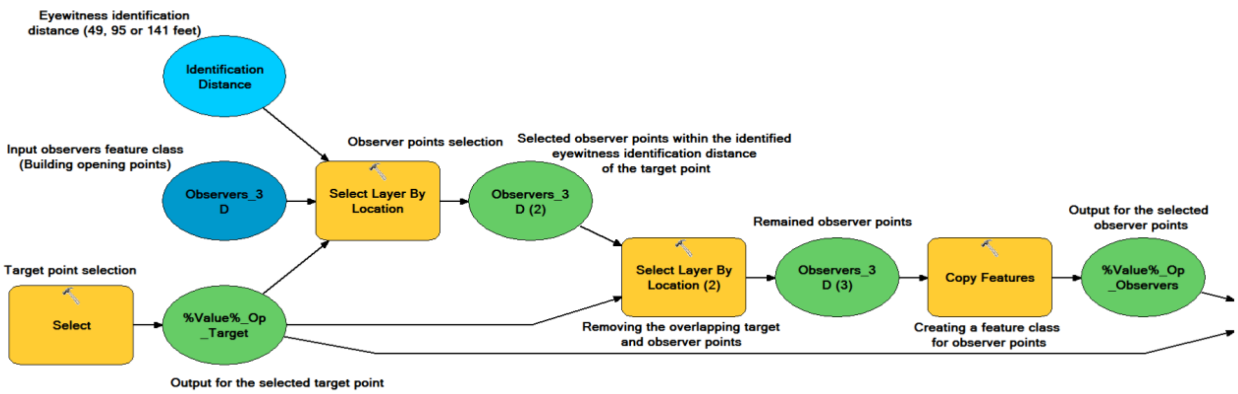


Figure 58. Chain of selecting observer points within a distance from a specified target point in the occupant surveillability model (Source: Author).

Table 33

Tools utilized for selecting observer points within a distance from a specified target point in the occupant surveillability model (Source: Author).

Tool	Parameters	
Select Layer By Location	Input Feature Layer	Observer_3D
	Relationship	Within a Distance
	Selecting features	%Value%_Op_Target
	Search Distance	Eyewitness identification distance
	Selection Type	New Selection
Select Layer By Location	Input Feature Layer	Observer_3D
	Relationship	Intersect
	Selecting features	%Value%_Op_Target
	Selection Type	Remove from Selection
Copy Features	Input Feature Layer	Observer_3D
	Output Feature Class	%Value%_Op_Observers

4.3.1.2 Constructing sightlines

The construct sight lines tool generates line features, representing sightlines from observer points to target points, target lines or target polygons (Esri, 2014a). This tool was utilized to create sightlines from a selected target point to observer points within a distance of that selected target (See Table 34 and *Figure 59*).

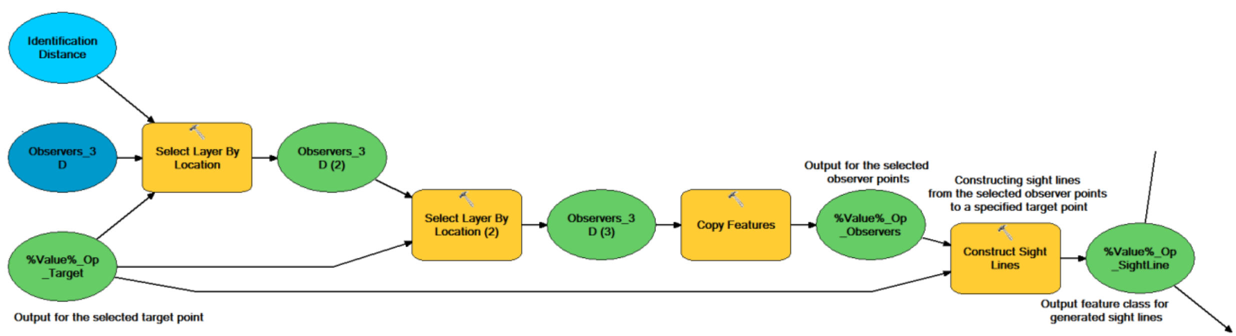


Figure 59. Chain of constructing sightlines from a specified target to selected observer points in the occupant surveillability model (Source: Author).

Table 34

Tool utilized for constructing sightlines from a specified target to selected observer points in the occupant surveillability model (Source: Author).

Tool	Parameters	
Construct Sight Lines	Observer Points	%Value%_Op_Observers
	Target Features	%Value%_Op_Target
	Output	%Value%_Op_SightLine
	Observer Height Field	HValue_Z
	Target Height Field	HValue_Z

4.3.1.3 Line of sight analysis

The line of sight tool computed visibility along the constructed sightlines. Analysis of visibility was based on an elevation surface (i.e. TIN, DEM, etc.). 3-dimensional Multipatch features (i.e. buildings, vegetation, visual barriers, etc.) were introduced as obstruction elements for analysis of visibility. Sightlines could be in-sight or out-of-sight depending on the elevation of land surface and obstructing features (Esri, 2014a).

When target or observer points were placed on outline or edges of buildings, the start and end point of sightlines would be located on edges of obstructing Multipatch features (here buildings surfaces). This circumstance raised an issue for visibility analysis as the line of sight tool could not determine which environment, the inside or outside of buildings was the obstructing and non-obstructing environment. I scaled the 3-dimensional building Multipatch features at 99% of their actual size. This way some space was created between start and end point of sightlines and 3-dimensional building features, resulting the urban environment to be considered the non-obstructing environment and inside of building Multipatch features to be the obstructing environment.

However, when 3-dimensional building features were scaled at 99% of their actual size, constructed sightlines from observer points to a specified target on the same surface were considered visible as they do not get obstructed by 3-dimensional building features. This issue was solved by adding buffers around building openings. Employing this method, sightlines generated from observers to a selected target on the same surface or facade were obstructed by buffers around building openings and considered invisible (See *Figure 60*).

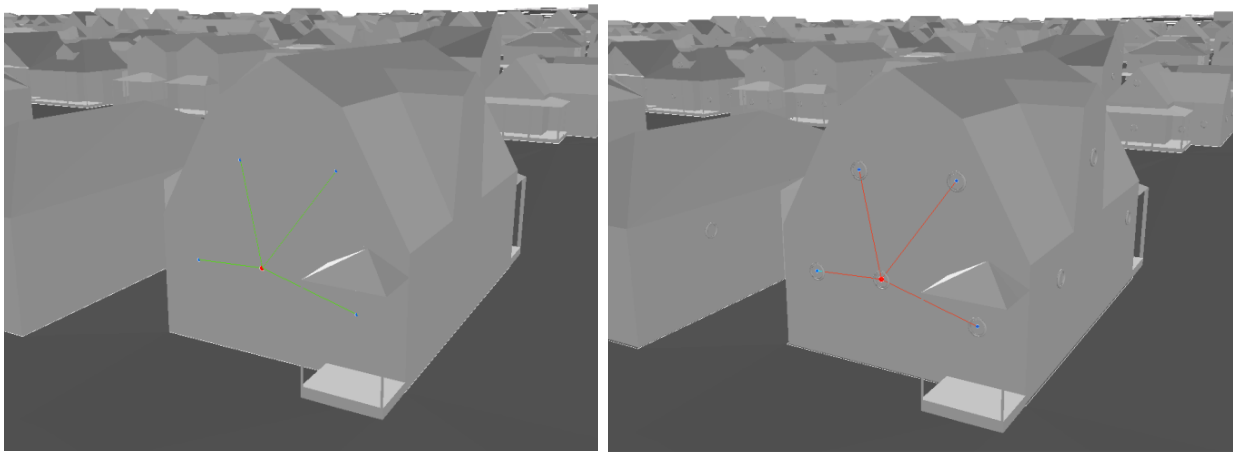


Figure 60. Visibility of building openings placed on same facade to each other. Left: Sightlines were considered visible before adding frames. Left: Sightlines were considered obstructed after adding frames (Source: Author).

The line of sight analysis tool was then utilized to compute visibility along sightlines on the West-Central TIN model. Individual or combinations of 3-dimentnional Multipatch features were introduced as obstructing feature(s) for analysis of visibility in different steps. After execution of the line of sight tool, three attributes indicating visibility information along sightlines were added to the output line feature class; "VisCode", "TarIsVis" and "OBSTR_MPID." "VisCode" field described visibility of segments along sightlines. "TarIsVis" field indicated visibility between target and observer points, and "OBSTR_MPID" displayed whether or not Multipatch features obstruct sightlines. Values of two fields could be used for selecting sightlines along which target and observer points could see each other; "TarIsVis" or "OBSTR_MPID". Here, the "TarIsVis" field was used for selecting sightlines along which target and observer points survey each other (See Table 35 and *Figure 61*).

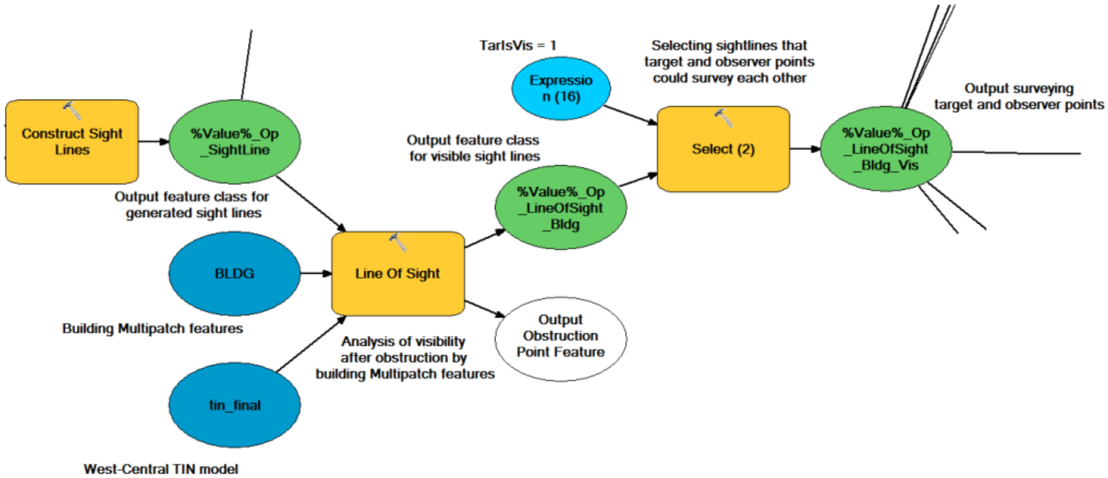


Figure 61. Chain of analyzing visibility and selecting sightlines along which target and observer points survey each other (Source: Author).

Table 35

Tools utilized for analysis of visibility and selecting sightlines along which target and observer points survey each other (Source: Author).

Tool	Parameters	
Line Of Sight	Input Surface	TIN_WestCentral
	Input Line Features	%Value%_Op_SightLine
	Input Features	Obstructing feature/s (See Table 30)
	Output Feature Class	%Value%_Op_LineOfSight_Name of obstructing feature/s
Select	Input Features	%Value%_Op_LineOfSight_Name of obstructing feature/s
	Output Feature Class	%Value%_Op_LineOfSight_Name of obstructing feature/s_Vis
	Expression	TarIsVis = 1 (or OBSTR_MPID = -9999)

I then computed 3-dimensional length of visible sightlines using the add Z information tool. And lastly, sightlines that were shorter or equal in length compared to my distance measures of surveillability were queried (See Table 36 and *Figure 62*). I then enumerated the number of visible sightlines according to their 2-dimensional and 3-dimensional length.

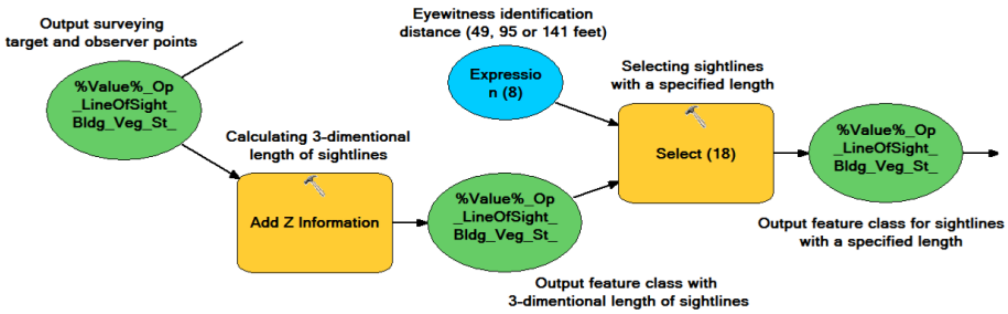


Figure 62. Chain of computing 3D length of sightlines and selecting sightlines within a specified surveillability distance (Source: Author).

Table 36

Tools utilized for computing length of sightlines in 3D and selecting sightlines within a specified surveillability distance (Source: Author).

Tool	Parameters	
Add Z Information	Input Features	%Value%_Op_LineOfSight_Name of obstructing feature/s_Vis
	Output Property	Length_3D
Select	Input Features	%Value%_Op_LineOfSight_Name of obstructing feature/s_Vis
	Output Feature Class	%Value%_Op_LineOfSight_Name of obstructing feature/s_Vis_Len
	Expression	Length3D <= surveillability distance

4.3.1.4 Summarizing statistics for sightlines

Each output file name in the occupant surveillability model had the unique identifier for each specified target point, the tools utilized and the obstruction features introduced as part of its name. I used the add field and calculate field tools to appended the file names to the attribute tables of the construct sight line and the line of sight analysis feature classes. Then, I summarized information on name, number of sightlines and minimum, maximum, mean and standard deviation length of sightlines for each target point in a table by utilizing the summary statistics tool (See Table 37, *Figure 63*, Figure 64 and Figure 65).

The summary statistics table for the construct sight line tool showed data on minimum, maximum, mean and standard deviation length of sightlines for each target point. The number of sightlines from the construct sight line tool represented the number of observer and target points that could have surveyed each other if no obstruction feature existed in the urban environment.

I computed visibility along sightlines by obstructing sightlines with individual or combinations of architectural and landscape features (See Table 30) to compute the extent to which various architectural and landscape feature vary measures of surveillability (See Appendix C). Data on minimum, maximum, mean and standard deviation length of visible sightlines after obstruction by architectural and landscape features were also recorded.

Two summary statistics table were generated for the line of sight tool. One showed the number and minimum, maximum, mean and standard deviation length of visible sightlines for each building opening taking into account length of 3-dimentional sightlines in 2-dimentions. The other showed the number and minimum, maximum, mean and standard deviation length of visible sightlines in 3-dimensions after restricting lengths by surveillability distance measures.

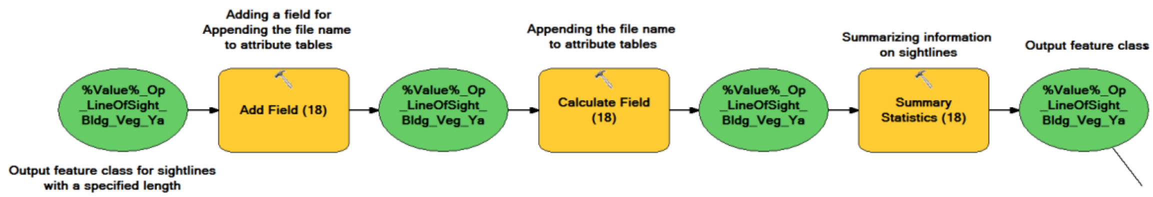
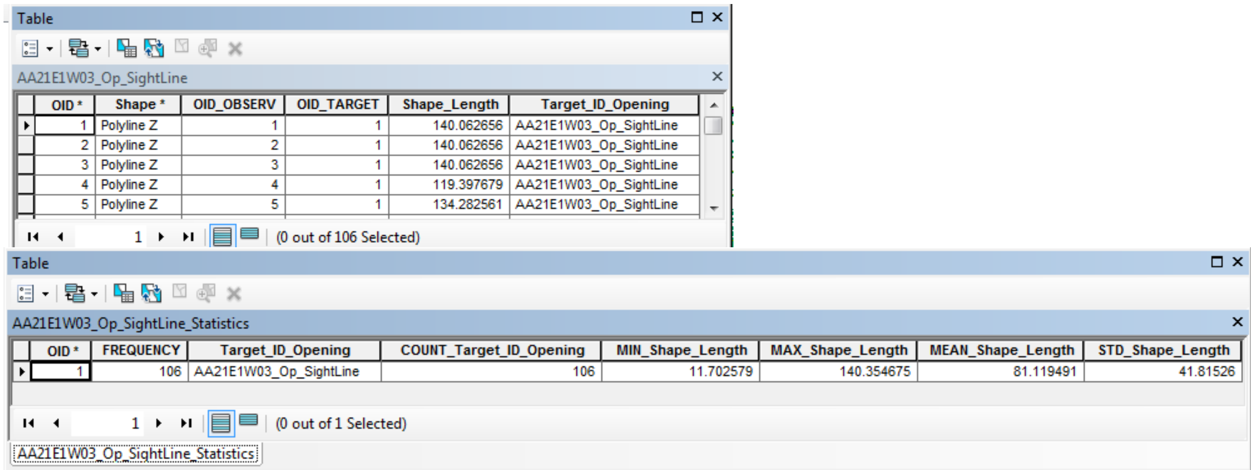


Figure 63. Chain of appending file names to the attribute tables of the construct sight line and the line of sight analysis feature classes and creating summary statistics (Source: Author).

Table 37

Tools utilized for appending file names to the attribute tables of the construct sight line and the line of sight analysis feature classes and creating summary statistics (Source: Author).

Tool	Parameters	
Add Field	Input Table	%Value%_Op_SightLine OR %Value%_Op_LineOfSight_ Name of obstructing feature/s_Vis_Len
	Field Name	Target_ID_Opening
	Field Type	Text
Calculate Field	Input Table	%Value%_Op_SightLine OR %Value%_Op_LineOfSight_ Name of obstructing feature/s_Vis_Len
	Field Name	Target_ID_Opening
	Expression	"%Value%_Op_SightLine" OR "%Value%_Op_LineOfSight_ Name of obstructing feature/s_Vis_Len"
Summary Statistics	Input Table	%Value%_Op_SightLine OR %Value%_Op_LineOfSight_ Name of obstructing feature/s_Vis_Len
	Output Table	%Value%_Op_SightLine_Statistics OR %Value%_Op_LineOfSight_ Name of obstructing feature/s_Vis_Len_Statistics
	Statistics Field(s)	Statistics Type
	Target_ID_Opening	First
	Target_ID_Opening	Count
	Shape_Length	Minimum, Maximum, Mean, Standard Deviation



Table

AA21E1W03_Op_SightLine

OID *	Shape *	OID_OBSERV	OID_TARGET	Shape_Length	Target_ID_Opening
1	Polyline Z	1	1	140.062656	AA21E1W03_Op_SightLine
2	Polyline Z	2	1	140.062656	AA21E1W03_Op_SightLine
3	Polyline Z	3	1	140.062656	AA21E1W03_Op_SightLine
4	Polyline Z	4	1	119.397679	AA21E1W03_Op_SightLine
5	Polyline Z	5	1	134.282561	AA21E1W03_Op_SightLine

(0 out of 106 Selected)

Table

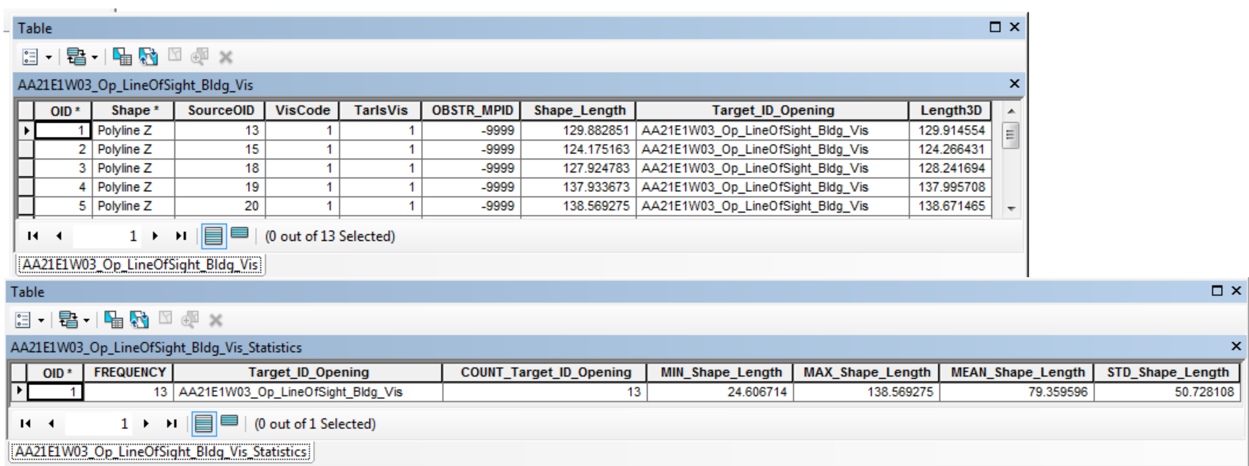
AA21E1W03_Op_SightLine_Statistics

OID *	FREQUENCY	Target_ID_Opening	COUNT_Target_ID_Opening	MIN_Shape_Length	MAX_Shape_Length	MEAN_Shape_Length	STD_Shape_Length
1	106	AA21E1W03_Op_SightLine	106	11.702579	140.354675	81.119491	41.81526

(0 out of 1 Selected)

AA21E1W03_Op_SightLine_Statistics

Figure 64. Output tables for the construct sight line and summary statistics tools (Source: Author).



Table

AA21E1W03_Op_LineOfSight_Bldg_Vis

OID *	Shape *	SourceOID	VisCode	TarIsVis	OBSTR_MPID	Shape_Length	Target_ID_Opening	Length3D
1	Polyline Z	13	1	1	-9999	129.882851	AA21E1W03_Op_LineOfSight_Bldg_Vis	129.914554
2	Polyline Z	15	1	1	-9999	124.175163	AA21E1W03_Op_LineOfSight_Bldg_Vis	124.266431
3	Polyline Z	18	1	1	-9999	127.924783	AA21E1W03_Op_LineOfSight_Bldg_Vis	128.241694
4	Polyline Z	19	1	1	-9999	137.933673	AA21E1W03_Op_LineOfSight_Bldg_Vis	137.995708
5	Polyline Z	20	1	1	-9999	138.569275	AA21E1W03_Op_LineOfSight_Bldg_Vis	138.671465

(0 out of 13 Selected)

AA21E1W03_Op_LineOfSight_Bldg_Vis

Table

AA21E1W03_Op_LineOfSight_Bldg_Vis_Statistics

OID *	FREQUENCY	Target_ID_Opening	COUNT_Target_ID_Opening	MIN_Shape_Length	MAX_Shape_Length	MEAN_Shape_Length	STD_Shape_Length
1	13	AA21E1W03_Op_LineOfSight_Bldg_Vis	13	24.606714	138.569275	79.359596	50.728108

(0 out of 1 Selected)

AA21E1W03_Op_LineOfSight_Bldg_Vis_Statistics

Figure 65. Output tables for the line of sight analysis and summary statistics tools (Source: Author).

4.3.1.5 Creating occupant surveillability table

The last step in the occupant surveillability model was comprised of combining visibility characteristics of each target point in a single table or spread sheet. The merge tool was utilized to combine 17 summary statistics tables (1 from the construct sight line tool and 16 from the line of sight tool) in a single table. Four other tools were consequently utilized to add two fields to the merged table and split the output file name into the unique identifier for each target point and a description representing surveillability category, scenario and tools utilized (See Table 38, *Figure 66* and *Figure 67*).

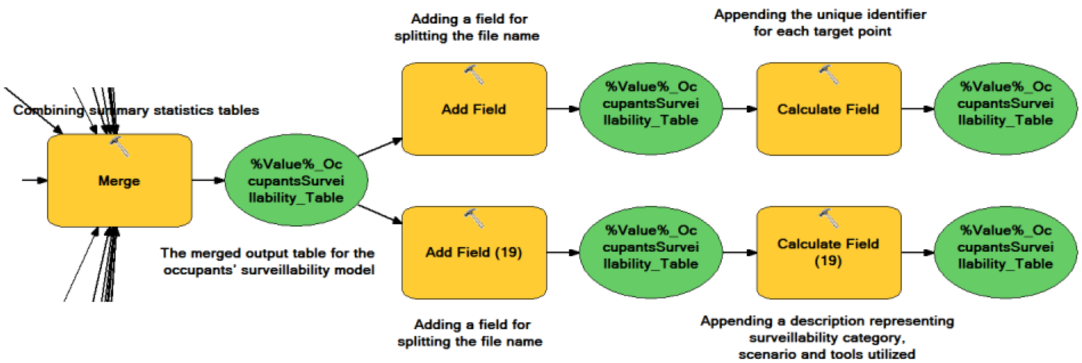
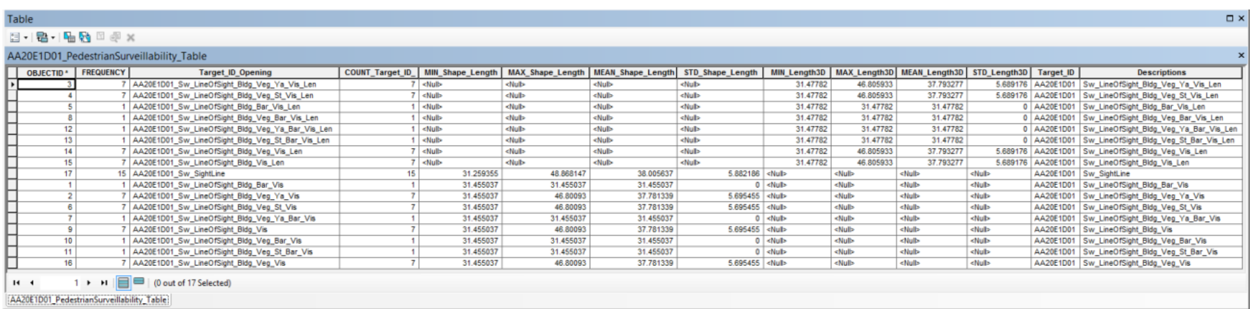


Figure 66. Chain of combing visibility characteristics of each target point in a single table and splitting and storing the output file name into two fields (Source: Author).

Table 38

Merging visibility characteristics of sightlines in a single table and splitting and storing the output file name into two fields (Source: Author).

Tool	Parameters	
Merge	Input Datasets	Tables for the construct sight line and line of sight analysis
	Output Dataset	%Value%_OccupantsSurveillability_Table
Add Field	Input Table	%Value%_OccupantsSurveillability_Table
	Field Name	Target_ID
	Field Type	Text
Calculate Field	Input Table	%Value%_OccupantsSurveillability_Table
	Field Name	Target_ID
	Expression	Left([FIRST_Target_ID_Opening],9[23])
Add Field	Input Table	%Value%_OccupantsSurveillability_Table
	Field Name	Descriptions
	Field Type	Text
Calculate Field	Input Table	%Value%_OccupantsSurveillability_Table
	Field Name	Target_ID
	Expression	Mid([FIRST_Target_ID_Opening],11[24])



Table

AA20E1D01_PedestrianSurveillability_Table

OBJECTID *	FREQUENCY	Target_ID_Opening	COUNT_Target_ID_	MIN_Shape_Length	MAX_Shape_Length	MEAN_Shape_Length	STD_Shape_Length	MIN_Length3D	MAX_Length3D	MEAN_Length3D	STD_Length3D	Target_ID	Descriptions
3	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len	7	<Null>	<Null>	<Null>	<Null>	31.47782	46.805933	37.793277	5.689176	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len
4	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_St_Vis_Len	7	<Null>	<Null>	<Null>	<Null>	31.47782	46.805933	37.793277	5.689176	AA20E1D01	Sw_LineOfSight_Bldg_Veg_St_Vis_Len
5	1	AA20E1D01_Sw_LineOfSight_Bldg_Bar_Vis_Len	1	<Null>	<Null>	<Null>	<Null>	31.47782	31.47782	31.47782	0	AA20E1D01	Sw_LineOfSight_Bldg_Bar_Vis_Len
8	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len	1	<Null>	<Null>	<Null>	<Null>	31.47782	31.47782	31.47782	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len
12	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	1	<Null>	<Null>	<Null>	<Null>	31.47782	31.47782	31.47782	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len
13	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	1	<Null>	<Null>	<Null>	<Null>	31.47782	31.47782	31.47782	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len
14	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Vis_Len	7	<Null>	<Null>	<Null>	<Null>	31.47782	46.805933	37.793277	5.689176	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Vis_Len
15	7	AA20E1D01_Sw_LineOfSight_Bldg_Vis_Len	7	<Null>	<Null>	<Null>	<Null>	31.47782	46.805933	37.793277	5.689176	AA20E1D01	Sw_LineOfSight_Bldg_Vis_Len
17	15	AA20E1D01_Sw_SightLine	15	31.259355	48.868147	38.005637	5.882186	<Null>	<Null>	<Null>	<Null>	AA20E1D01	Sw_SightLine
1	1	AA20E1D01_Sw_LineOfSight_Bldg_Bar_Vis	1	31.455037	31.455037	31.455037	0	<Null>	<Null>	<Null>	<Null>	AA20E1D01	Sw_LineOfSight_Bldg_Bar_Vis
2	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Ya_Vis	7	31.455037	46.80093	37.781339	5.695455	<Null>	<Null>	<Null>	<Null>	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Ya_Vis
6	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_St_Vis	7	31.455037	46.80093	37.781339	5.695455	<Null>	<Null>	<Null>	<Null>	AA20E1D01	Sw_LineOfSight_Bldg_Veg_St_Vis
7	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis	1	31.455037	31.455037	31.455037	0	<Null>	<Null>	<Null>	<Null>	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis
9	7	AA20E1D01_Sw_LineOfSight_Bldg_Vis	7	31.455037	46.80093	37.781339	5.695455	<Null>	<Null>	<Null>	<Null>	AA20E1D01	Sw_LineOfSight_Bldg_Vis
10	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Bar_Vis	1	31.455037	31.455037	31.455037	0	<Null>	<Null>	<Null>	<Null>	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Bar_Vis
11	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_St_Bar_Vis	1	31.455037	31.455037	31.455037	0	<Null>	<Null>	<Null>	<Null>	AA20E1D01	Sw_LineOfSight_Bldg_Veg_St_Bar_Vis
16	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Vis	7	31.455037	46.80093	37.781339	5.695455	<Null>	<Null>	<Null>	<Null>	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Vis

1 (0 out of 17 Selected)

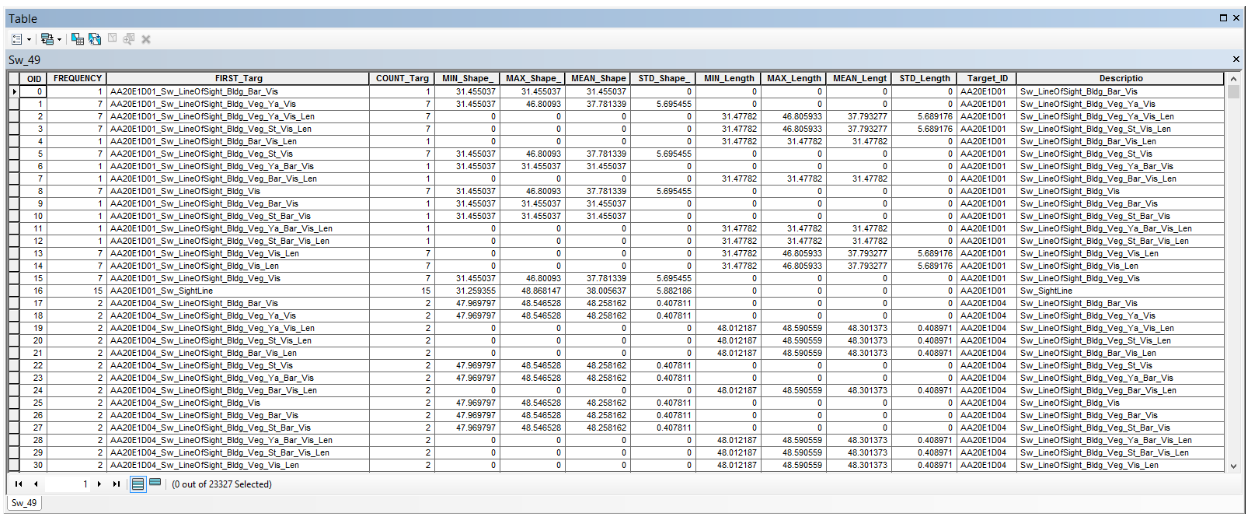
AA20E1D01_PedestrianSurveillability_Table

Figure 67. Output table showing visibility characteristics of a building opening (Source: Author).

[23] Unique identifiers for each opening consist of a 9 letter long string.

[24] Descriptions on surveillability category, scenario and tools employed for analysis of visibility starts from the 11th letter of the output name.

After successful execution of the occupant surveillability model, each potential target had a summary statistics table representing its visibility characteristics. Having 3,179 potential target points (each having one table similar to *Figure 67*), I utilized the merge tool again to combine summary statistics tables of all potential target points into a single table (See *Figure 68*). In brief, 9 summary tables were created representing surveillability characteristics of building openings for the occupant, road and pedestrian surveillability categories within 49, 95 and 141 feet of building openings.



Table

Sw_49

OID	FREQUENCY	FIRST_Targ	COUNT_Targ	MIN_Shape_	MAX_Shape_	MEAN_Shape	STD_Shape_	MIN_Length	MAX_Length	MEAN_Lengt	STD_Length	Target_ID	Descriptio
0	1	AA20E1D01_Sw_LineOfSight_Bldg_Bar_Vis	1	31.455037	31.455037	31.455037	0	0	0	0	0	AA20E1D01	Sw_LineOfSight_Bldg_Bar_Vis
1	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Ya_Vis	7	31.455037	46.80093	37.781339	5.695455	0	0	0	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Ya_Vis
2	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len	7	0	0	0	0	31.47782	46.805933	37.793277	5.689176	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len
3	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_St_Vis_Len	7	0	0	0	0	31.47782	46.805933	37.793277	5.689176	AA20E1D01	Sw_LineOfSight_Bldg_Veg_St_Vis_Len
4	1	AA20E1D01_Sw_LineOfSight_Bldg_Bar_Vis_Len	1	0	0	0	0	31.47782	31.47782	31.47782	0	AA20E1D01	Sw_LineOfSight_Bldg_Bar_Vis_Len
5	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_St_Vis	7	31.455037	46.80093	37.781339	5.695455	0	0	0	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_St_Vis
6	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis	1	31.455037	31.455037	31.455037	0	0	0	0	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis
7	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len	1	0	0	0	0	31.47782	31.47782	31.47782	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len
8	7	AA20E1D01_Sw_LineOfSight_Bldg_Vis	7	31.455037	46.80093	37.781339	5.695455	0	0	0	0	AA20E1D01	Sw_LineOfSight_Bldg_Vis
9	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Bar_Vis	1	31.455037	31.455037	31.455037	0	0	0	0	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Bar_Vis
10	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_St_Bar_Vis	1	31.455037	31.455037	31.455037	0	0	0	0	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_St_Bar_Vis
11	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	1	0	0	0	0	31.47782	31.47782	31.47782	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len
12	1	AA20E1D01_Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	1	0	0	0	0	31.47782	31.47782	31.47782	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len
13	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Vis_Len	7	0	0	0	0	31.47782	46.805933	37.793277	5.689176	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Vis_Len
14	7	AA20E1D01_Sw_LineOfSight_Bldg_Vis_Len	7	0	0	0	0	31.47782	46.805933	37.793277	5.689176	AA20E1D01	Sw_LineOfSight_Bldg_Vis_Len
15	7	AA20E1D01_Sw_LineOfSight_Bldg_Veg_Vis	7	31.455037	46.80093	37.781339	5.695455	0	0	0	0	AA20E1D01	Sw_LineOfSight_Bldg_Veg_Vis
16	15	AA20E1D01_Sw_SightLine	15	31.259355	48.868147	38.005637	5.882186	0	0	0	0	AA20E1D01	Sw_SightLine
17	2	AA20E1D04_Sw_LineOfSight_Bldg_Bar_Vis	2	47.969797	48.546528	48.258162	0.407811	0	0	0	0	AA20E1D04	Sw_LineOfSight_Bldg_Bar_Vis
18	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_Ya_Vis	2	47.969797	48.546528	48.258162	0.407811	0	0	0	0	AA20E1D04	Sw_LineOfSight_Bldg_Veg_Ya_Vis
19	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len	2	0	0	0	0	48.012187	48.590559	48.301373	0.408971	AA20E1D04	Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len
20	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_St_Vis_Len	2	0	0	0	0	48.012187	48.590559	48.301373	0.408971	AA20E1D04	Sw_LineOfSight_Bldg_Veg_St_Vis_Len
21	2	AA20E1D04_Sw_LineOfSight_Bldg_Bar_Vis_Len	2	0	0	0	0	48.012187	48.590559	48.301373	0.408971	AA20E1D04	Sw_LineOfSight_Bldg_Bar_Vis_Len
22	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_St_Vis	2	47.969797	48.546528	48.258162	0.407811	0	0	0	0	AA20E1D04	Sw_LineOfSight_Bldg_Veg_St_Vis
23	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis	2	47.969797	48.546528	48.258162	0.407811	0	0	0	0	AA20E1D04	Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis
24	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len	2	0	0	0	0	48.012187	48.590559	48.301373	0.408971	AA20E1D04	Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len
25	2	AA20E1D04_Sw_LineOfSight_Bldg_Vis	2	47.969797	48.546528	48.258162	0.407811	0	0	0	0	AA20E1D04	Sw_LineOfSight_Bldg_Vis
26	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_Bar_Vis	2	47.969797	48.546528	48.258162	0.407811	0	0	0	0	AA20E1D04	Sw_LineOfSight_Bldg_Veg_Bar_Vis
27	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_St_Bar_Vis	2	47.969797	48.546528	48.258162	0.407811	0	0	0	0	AA20E1D04	Sw_LineOfSight_Bldg_Veg_St_Bar_Vis
28	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	2	0	0	0	0	48.012187	48.590559	48.301373	0.408971	AA20E1D04	Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len
29	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	2	0	0	0	0	48.012187	48.590559	48.301373	0.408971	AA20E1D04	Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len
30	2	AA20E1D04_Sw_LineOfSight_Bldg_Veg_Vis_Len	2	0	0	0	0	48.012187	48.590559	48.301373	0.408971	AA20E1D04	Sw_LineOfSight_Bldg_Veg_Vis_Len

1 (0 out of 23327 Selected)

Sw_49

Figure 68. Output table showing occupant surveillability characteristics of building openings (Source: Author).

4.3.2 Road and Pedestrian Surveillability ModelBuilder

The road and pedestrian surveillability models computed surveillability of building openings as seen by a potential criminal in cars or while walking. The road and pedestrian surveillability models were similar to the occupant surveillability model with the exception of 3-dimensional points representing road centerlines (for the road surveillability model) and 3-dimensional points representing curblines (for the pedestrian surveillability) model constituting observer points. Target points and 3-dimensional Multipatch features were consistent along the occupant, road and pedestrian surveillability models. The following section elaborates on selection of observer points in the road and pedestrian surveillability models. All other procedures for computing surveillability resembled to that of the occupant surveillability model and are not discussed.

4.3.2.1 Iteration, selection and inline variables

The road and pedestrian surveillability models (like the occupant surveillability model) began with feeding the same target points feature class into a row iterator. A point feature class was created as the row iterator loops sequentially through the table of targets points and selected one record. The unique identifier for target building openings was also set as inline variable (%Value%) in subsequent tools (See Table 39 and *Figure 69*).

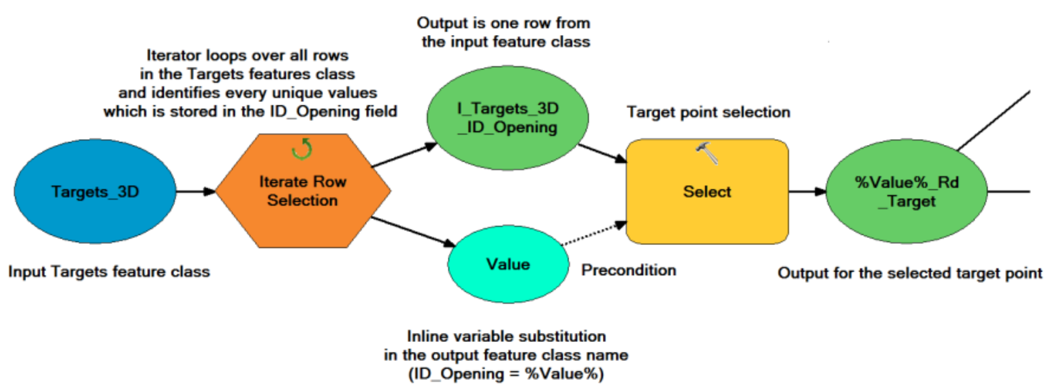


Figure 69. Chain of iteration and inline variable substitution in the road and pedestrian surveillability model (Source: Author).

Table 39

Tools utilized for iteration and inline variable substitution in the road and pedestrian surveillability model (Source: Author).

Tool	Parameters	
Iterate Row Selection	Input Table	Targets_3D
	Group by Fields	ID_Opening
Select	Input Features	I_Targets_3D_ID_Opening
	Output Feature Class	%Value%_Rd(Sw)_Target

Next, each selected target point was transferred into the select layer by location tool, where points representing road centerlines or curblines within a distance of a specified target point were selected. Observer points to a target point were then copied and fed into the construct sight line tool along with the selected target point (See Table 40 and *Figure 70*).

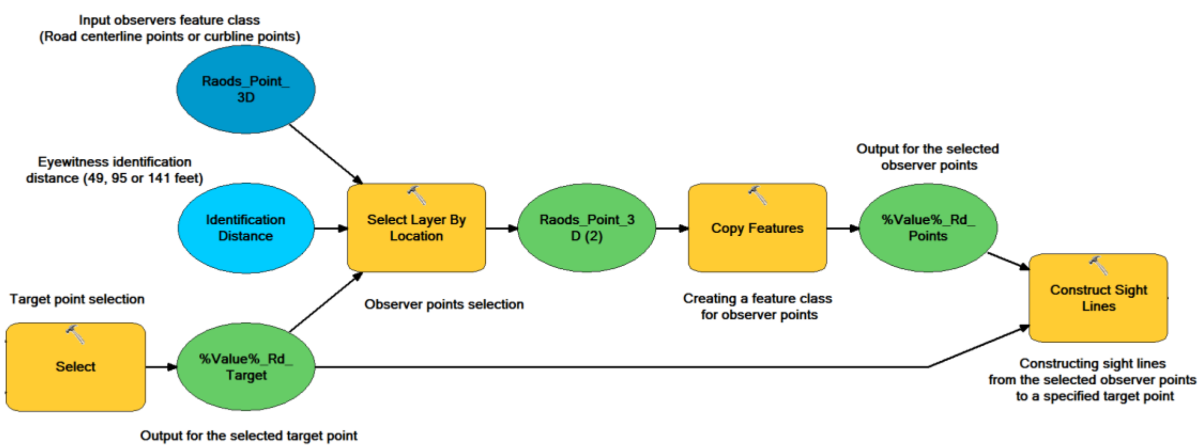


Figure 70. Chain of selecting observer points within a distance from a specified target point in the road and pedestrian surveillability model (Source: Author).

Table 40

Tools utilized for selecting observer points within a distance from a specified target point in the road and pedestrian surveillability model (Source: Author).

Tool	Parameters	
Select Layer By Location	Input Feature Layer	RoadCenterline_Points_3D OR CurblinePoints_3D
	Relationship	Within a Distance
	Selecting features	%Value%_Rd(Sw)_Target
	Search Distance	Eyewitness identification distance
	Selection Type	New Selection
Copy Features	Input Feature Layer	RoadCenterline_Points_3D OR CurblinePoints_3D
	Output Feature Class	%Value%_Rd(Sw)_Observers

All other procedures from constructing sightlines to computing visibility along sightlines, and from creating summary statistics tables for possible and visible sightlines to merging summary statistics tables of all target points into a single table resembled to that of the occupant surveillability model. In the last section for this chapter, I listed the name and description of all intermediate and final output feature classes or tables from the occupant, road and pedestrian surveillability models (See Table 41).

4.4 Summary

I automated the process of quantifying occupant, road and pedestrian surveillability through utilization of ESRI ModelBuilder. I was able to automate this computation process without writing codes by using ESRI ModelBuilder. ModelBuilder also enabled me to document and share my GIS process, and rerun the model at any time. However, some models like mine are graphic and processor intensive, require a powerful machine to run and take a long time to execute.

Table 41

Outputs from the occupant surveillability, pedestrian surveillability and road surveillability models (Source: Author).

Scenarios/Description	Outputs
Point Feature Classes	%Value%_Op/Rd/Sw_Target %Value%_Op/Rd/Sw_Observers
Sightlines	%Value%_Op/Rd/Sw_SightLine %Value%_Op/Rd/Sw_SightLine_Statistics
Line of Sight for Buildings (+ Myopic Distance)	%Value%_Op/Rd/Sw_LineOfSight_Bldg %Value%_Op/Rd/Sw_LineOfSight_Bldg_Vis %Value%_Op/Rd/Sw_LineOfSight_Bldg_Vis_Len %Value%_Op/Rd/Sw_LineOfSight_Bldg_Vis_Statistics %Value%_Op/Rd/Sw_LineOfSight_Bldg_Vis_Len_Statistics
Line of Sight for Buildings + Yard Vegetation (+ Myopic Distance)	%Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Ya %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Ya_Vis %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Ya_Vis_Statistics %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len_Statistics
Line of Sight for Buildings + Street Vegetation (+ Myopic Distance)	%Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_St %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_St_Vis %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_St_Vis_Len %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_St_Vis_Statistics %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_St_Vis_Len_Statistics
Line of Sight for Buildings + Visual Barriers (+ Myopic Distance)	%Value%_Op/Rd/Sw_LineOfSight_Bldg_Bar %Value%_Op/Rd/Sw_LineOfSight_Bldg_Bar_Vis %Value%_Op/Rd/Sw_LineOfSight_Bldg_Bar_Vis_Len %Value%_Op/Rd/Sw_LineOfSight_Bldg_Bar_Vis_Statistics %Value%_Op/Rd/Sw_LineOfSight_Bldg_Bar_Vis_Len_Statistics

Line of Sight for Buildings + Yard Vegetation + Visual Barriers (+ Myopic Distance)	%Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Ya_Bar %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Statistics %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len_Statistics
Line of Sight for Buildings + Street Vegetation + Visual Barriers (+ Myopic Distance)	%Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_St_Bar %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_St_Bar_Vis %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Statistics %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len_Statistics
Line of Sight for Buildings + Yard Vegetation + Street Vegetation (+ Myopic Distance)	%Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Vis %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Vis_Len %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Vis_Statistics %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Vis_Len_Statistics
Line of Sight for Buildings + Yard Vegetation + Street Vegetation + Visual Barriers (+ Myopic Distance)	%Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Bar %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Bar_Vis %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Bar_Vis_Statistics %Value%_Op/Rd/Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len_Statistics
Outputs from ModelBuilders	%Value%_OccupantsSurveillability_Table %Value%_RoadSurveillability_Table %Value%_PedestrianSurveillability_Table
Merged Tables	OccupantsSurveillability_Table RoadSurveillability_Table PedestrianSurveillability_Table

5 STATISTICAL ANALYSIS AND RESULTS

5.1 Introduction

This chapter concentrates on the analytic results for the relationship between natural surveillance and residential burglary commissions and residential burglaries. I then employed descriptive and inferential statistics for exploring this relationship at two levels of building opening and building structure. The results of Spearman's rank correlation, Mann-Whitney U and binary logistic regression are discussed in detail.

5.2 Statistical Analysis

Descriptive and inferential statistical analyses for this section of this study were carried out in IBM® SPSS® Statistics Premium GradPack (Student Version 22) in the windows environment, with alpha or level of significance for inferential statistics set at 0.05. I analyzed the relationship between natural surveillance and burglary commissions and residential burglaries at two levels of building opening and building to investigate vulnerability of building openings and residential dwellings for breaking and entering purposes. At the building opening level, I first analyzed building openings, followed by stratifying building openings to door openings and window openings to separately study surveillability characteristics and vulnerability of each group to burglary commissions. The results of analysis are shown according to distance measures of surveillability (i.e. 49, 95 and 141 feet).

The statistical analyses conducted for this study are Spearman's rank correlation, Mann-Whitney U and binary logistic regressions. I proposed the following measures at the building opening and building level:

- Descriptive statistics (mean, mode, standard deviation, minimum and maximum number of sightlines) for occupant, road and pedestrian surveillability for building openings and buildings.
- Spearman's rank correlation to determine the relationship between the degree of occupant, road and pedestrian surveillability and burglary commissions (at the building opening level) or residential burglaries (at the building level).
- Mann-Whitney U test to determine whether the degree of occupant, road and pedestrian surveillability differ between burglarized and non-burglarized building openings and buildings.
- Binary logistic regressions to make predictions regarding the most likely entry points of burglaries (at the building opening level) or residential burglaries (at the building level) from the knowledge of occupant, road and pedestrian surveillability.

5.3 Statistical Analysis at the Building Opening Level

The following sections discuss the relationship between the degree of natural surveillance and commission of residential burglaries at the finest imaginable scale - building openings. I first analyzed vulnerability of building openings to burglary commissions, followed by stratifying building openings to door openings and window openings and studying surveillability characteristics and vulnerability of each group to burglary commissions independently.

5.3.1 Descriptive statistics

The following section offers a breadth of information on descriptive statistics. The SPSS explore procedure was first conducted to identify missing values and outliers, and to evaluate normality of independent variables. No missing values were observed. However, visual inspection of the histogram and assessment of skeweness and kurtosis values indicated the distribution of occupant, road and pedestrian surveillability at three distances of 49, 95 and 141 feet is positively skewed, with most of the scores on the lowest range (i.e. zero). In addition, the results of the Kolmogorov-Smirnov tests showed that none of the distributions are normal. Thus, I used non-parametric tests and techniques robust to violations of normality for statistical analysis. Descriptive statistics are categorized according to distance measures of surveillability and tabulated in Table 42, Table 43 and Table 44.

5.3.1.1 Within 49 feet distance

All building openings. Occupant surveillability of all building openings (i.e. doors and windows) ranged from 0 to 17, with a mean of 2.27 (n = 3179, SD = 2.60). Burglarized building openings had lower mean of occupant surveillability (n = 65, M = 1.17, SD = 1.90) than non-burglarized building openings (n = 3114, M = 2.29, SD = 2.61). In addition, the number of visible sightlines to burglarized building openings ranged from 0 and 7, while that number ranged from 0 and 17 for non-burglarized building openings.

Road surveillability of all building openings (i.e. doors and windows) ranged from 0 to 9, with a mean of 0.47 (n = 3179, SD = 1.30). Burglarized building openings had higher mean of road surveillability (n = 65, M = 0.82, SD = 1.78) than non-burglarized building openings (n =

3114, M = 0.46, SD = 1.28). Range of visible sightlines for burglarized and non-burglarized building openings was almost identical.

Pedestrian surveillability of all building openings (i.e. doors and windows) ranged from 0 to 27, with a mean of 4.06 (n = 3179, SD = 5.98). Burglarized building openings had higher mean of pedestrian surveillability (n = 65, M = 5.29, SD = 6.69) than non-burglarized building openings (n = 3114, M = 4.03, SD = 5.96). Range of visible sightlines for burglarized and non-burglarized building openings was almost identical.

Door openings. Occupant surveillability of door openings ranged from 0 to 12, with a mean of 1.31 (n = 648, SD = 1.97). Burglarized door openings had lower mean of occupant surveillability (n = 46, M = 1.20, SD = 1.90) than non-burglarized door openings (n = 602, M = 1.32, SD = 1.97). In addition, the number of visible sightlines to burglarized door openings ranged from 0 and 6, while that number ranged from 0 and 12 for non-burglarized door openings.

Road surveillability of door openings ranged from 0 to 7, with a mean of 0.36 (n = 648, SD = 1.04). Burglarized door openings had higher mean of road surveillability (n = 46, M = 0.85, SD = 1.69) than non-burglarized door openings (n = 602, M = 0.32, SD = 0.96). Range of visible sightlines for burglarized and non-burglarized door openings was almost identical.

Pedestrian surveillability of door openings ranged from 0 to 23, with a mean of 4.33 (n = 648, SD = 5.78). Burglarized door openings had higher mean of pedestrian surveillability (n = 46, M = 5.17, SD = 6.44) than non-burglarized door openings (n = 602, M = 4.27, SD = 5.72). Range of visible sightlines for burglarized and non-burglarized door openings was almost identical.

Window openings. Occupant surveillability of window openings ranged from 0 to 17, with a mean of 2.51 (n = 2531, SD = 2.68). Burglarized window openings had lower mean of occupant surveillability (n = 19, M = 1.11, SD = 1.91) than non-burglarized window openings (n = 2512, M = 2.52, SD = 2.68). In addition, the number of visible sightlines to burglarized window openings ranged from 0 and 7, while that number ranged from 0 and 17 for non-burglarized window openings.

Road surveillability of window openings ranged from 0 to 9, with a mean of 0.50 (n = 2531, SD = 1.35). Burglarized window openings had higher mean of road surveillability (n = 19, M = 0.74, SD = 2.02) than non-burglarized window openings (n = 2512, M = 0.50, SD = 1.35). Range of visible sightlines for burglarized and non-burglarized window openings was almost identical.

Pedestrian surveillability of window openings ranged from 0 to 27, with a mean of 3.98 (n = 2531, SD = 6.03). Burglarized window openings had higher mean of pedestrian surveillability (n = 19, M = 5.58, SD = 7.46) than non-burglarized window openings (n = 2512, M = 3.97, SD = 6.02). Range of visible sightlines for burglarized and non-burglarized window openings was almost identical.

In summary, burglarized building openings, door openings and window openings had lower degrees of occupant surveillability compared to non-burglarized ones. In addition, higher degrees of road and pedestrian surveillability was observed for burglarized building openings, door openings and window openings compared to non-burglarized ones.

Table 42

Descriptive statistics for occupant, road and pedestrian surveillability within 49 feet of building openings (Source: Author).

	49 feet					
Independent Variables	N	Mean	Mode	SD	Min	Max
Occupant surveillability	3179	2.27	0	2.60	0	17
Road surveillability	3179	0.47	0	1.30	0	9
Pedestrian surveillability	3179	4.06	0	5.98	0	27
Occupant surveillability (Door)	648	1.31	0	1.97	0	12
Road surveillability (Door)	648	0.36	0	1.04	0	7
Pedestrian surveillability (Door)	648	4.33	0	5.78	0	23
Occupant surveillability (Window)	2531	2.51	0	2.68	0	17
Road surveillability (Window)	2531	0.50	0	1.35	0	9
Pedestrian surveillability (Window)	2531	3.98	0	6.03	0	27

	49 feet burglarized						49 feet not burglarized					
Independent Variables	N	Mean	Mode	SD	Min	Max	N	Mean	Mode	SD	Min	Max
Occupant surveillability	65	1.17	0	1.90	0	7	3114	2.29	0	2.61	0	17
Road surveillability	65	0.82	0	1.78	0	8	3114	0.46	0	1.28	0	9
Pedestrian surveillability	65	5.29	0	6.69	0	25	3114	4.03	0	5.96	0	27
Occupant surveillability (Door)	46	1.20	0	1.92	0	6	602	1.32	0	1.97	0	12
Road surveillability (Door)	46	0.85	0	1.69	0	7	602	0.32	0	0.96	0	7
Pedestrian surveillability (Door)	46	5.17	0	6.44	0	21	602	4.27	0	5.72	0	23
Occupant surveillability (Window)	19	1.11	0	1.91	0	7	2512	2.52	0	2.68	0	17
Road surveillability (Window)	19	0.74	0	2.02	0	8	2512	0.50	0	1.35	0	9
Pedestrian surveillability (Window)	19	5.58	0	7.46	0	25	2512	3.97	0	6.02	0	27

5.3.1.2 Within 95 feet distance

All building openings. Occupant surveillability of all building openings (i.e. doors and windows) ranged from 0 to 25, with a mean of 3.43 (n = 3179, SD = 3.44). Burglarized building openings had lower mean of occupant surveillability (n = 65, M = 2.38, SD = 2.87) than non-burglarized building openings (n = 3114, M = 3.45, SD = 3.45). In addition, the number of visible sightlines to burglarized building openings ranged from 0 and 13, while that number ranged from 0 and 25 for non-burglarized building openings.

Road surveillability of all building openings (i.e. doors and windows) ranged from 0 to 19, with a mean of 4.53 (n = 3179, SD = 4.46). Burglarized building openings had higher mean of road surveillability (n = 65, M = 4.98, SD = 5.00) than non-burglarized building openings (n = 3114, M = 4.52, SD = 4.45). Range of visible sightlines for burglarized and non-burglarized building openings was almost identical.

Pedestrian surveillability of all building openings (i.e. doors and windows) ranged from 0 to 82, with a mean of 21.26 (n = 3179, SD = 20.21). Burglarized building openings had higher mean of pedestrian surveillability (n = 65, M = 23.23, SD = 22.28) than non-burglarized building openings (n = 3114, M = 21.22, SD = 20.16). Range of visible sightlines for burglarized and non-burglarized building openings was almost identical.

Door openings. Occupant surveillability of door openings ranged from 0 to 17, with a mean of 2.30 (n = 648, SD = 2.90). Burglarized door openings had higher mean of occupant surveillability (n = 46, M = 2.50, SD = 3.05) than non-burglarized door openings (n = 602, M = 2.28, SD = 2.89). In addition, the number of visible sightlines to burglarized door openings ranged from 0 and 13, while that number ranged from 0 and 17 for non-burglarized door openings.

Road surveillability of door openings ranged from 0 to 17, with a mean of 4.52 (n = 648, SD = 4.41). Burglarized door openings had higher mean of road surveillability (n = 46, M = 5.41, SD = 5.00) than non-burglarized door openings (n = 602, M = 4.45, SD = 4.35). Range of visible sightlines for burglarized and non-burglarized door openings was identical.

Pedestrian surveillability of door openings ranged from 0 to 79, with a mean of 21.72 (n = 648, SD = 21.04). Burglarized door openings had higher mean of pedestrian surveillability (n = 46, M = 24.72, SD = 23.44) than non-burglarized door openings (n = 602, M = 21.50, SD = 20.85). Range of visible sightlines for burglarized and non-burglarized door openings was identical.

Window openings. Occupant surveillability of window openings ranged from 0 to 25, with a mean of 3.72 (n = 2531, SD = 3.51). Burglarized window openings had lower mean of occupant surveillability (n = 19, M = 2.11, SD = 2.40) than non-burglarized window openings (n = 2512, M = 3.73, SD = 3.51). In addition, the number of visible sightlines to burglarized window openings ranged from 0 and 8, while that number ranged from 0 and 25 for non-burglarized window openings.

Road surveillability of window openings ranged from 0 to 19, with a mean of 4.53 (n = 2531, SD = 4.48). Burglarized window openings had lower mean of road surveillability (n = 19, M = 3.95, SD = 4.97) than non-burglarized window openings (n = 2512, M = 4.53, SD = 4.47).

Range of visible sightlines for burglarized and non-burglarized window openings was almost identical.

Pedestrian surveillability of window openings ranged from 0 to 82, with a mean of 21.14 (n = 2531, SD = 19.99). Burglarized window openings had lower mean of pedestrian surveillability (n = 19, M = 19.63, SD = 19.30) than non-burglarized window openings (n = 2512, M = 21.15, SD = 20.00). In addition, the number of visible sightlines to burglarized window openings ranged from 0 and 65, while that number ranged from 0 and 82 for non-burglarized window openings.

In summary, burglarized building openings and window openings had lower degrees of occupant surveillability compared to non-burglarized ones. Burglarized door openings had higher degrees of occupant surveillability compared to non-burglarized ones. In addition, burglarized building openings and door openings had higher degrees of road and pedestrian surveillability compared to non-burglarized ones. Burglarized window openings had lower degrees of road and pedestrian surveillability compared to non-burglarized ones.

Table 43

Descriptive statistics for occupant, road and pedestrian surveillability within 95 feet of building openings (Source: Author).

	95 feet					
Independent Variables	N	Mean	Mode	SD	Min	Max
Occupant surveillability	3179	3.43	0	3.44	0	25
Road surveillability	3179	4.53	0	4.46	0	19
Pedestrian surveillability	3179	21.26	0	20.21	0	82
Occupant surveillability (Door)	648	2.30	0	2.90	0	17
Road surveillability (Door)	648	4.52	0	4.41	0	17
Pedestrian surveillability (Door)	648	21.72	0	21.04	0	79
Occupant surveillability (Window)	2531	3.72	0	3.51	0	25
Road surveillability (Window)	2531	4.53	0	4.48	0	19
Pedestrian surveillability (Window)	2531	21.14	0	19.99	0	82

	95 feet burglarized						95 feet not burglarized					
Independent Variables	N	Mean	Mode	SD	Min	Max	N	Mean	Mode	SD	Min	Max
Occupant surveillability	65	2.38	0	2.87	0	13	3114	3.45	0	3.45	0	25
Road surveillability	65	4.98	0	5.00	0	18	3114	4.52	0	4.45	0	19
Pedestrian surveillability	65	23.23	0	22.28	0	79	3114	21.22	0	20.16	0	82
Occupant surveillability (Door)	46	2.50	0	3.05	0	13	602	2.28	0	2.89	0	17
Road surveillability (Door)	46	5.41	0	5.00	0	17	602	4.45	0	4.35	0	17
Pedestrian surveillability (Door)	46	24.72	0	23.44	0	79	602	21.50	0	20.85	0	79
Occupant surveillability (Window)	19	2.11	0	2.40	0	8	2512	3.73	0	3.51	0	25
Road surveillability (Window)	19	3.95	0,2	4.97	0	18	2512	4.53	0	4.47	0	19
Pedestrian surveillability (Window)	19	19.63	8	19.30	0	65	2512	21.15	0	20.00	0	82

5.3.1.3 Within 141 feet distance

All building openings. Occupant surveillability of all building openings (i.e. doors and windows) ranged from 0 to 36, with a mean of 8.65 (n = 3179, SD = 6.79). Burglarized building openings had lower mean of occupant surveillability (n = 65, M = 7.25, SD = 7.23) than non-burglarized building openings (n = 3114, M = 8.68, SD = 6.78). Range of visible sightlines for burglarized and non-burglarized building openings was almost identical.

Road surveillability of all building openings (i.e. doors and windows) ranged from 0 to 33, with a mean of 7.78 (n = 3179, SD = 7.65). Burglarized building openings had higher mean of road surveillability (n = 65, M = 8.55, SD = 8.53) than non-burglarized building openings (n = 3114, M = 7.77, SD = 7.63). Range of visible sightlines for burglarized and non-burglarized building openings was almost identical.

Pedestrian surveillability of all building openings (i.e. doors and windows) ranged from 0 to 139, with a mean of 37.36 (n = 3179, SD = 34.61). Burglarized building openings had higher mean of pedestrian surveillability (n = 65, M = 39.68, SD = 38.29) than non-burglarized building openings (n = 3114, M = 37.31, SD = 34.54). Range of visible sightlines for burglarized and non-burglarized building openings was almost identical.

Door openings. Occupant surveillability of door openings ranged from 0 to 35, with a mean of 7.83 (n = 648, SD = 6.99). Burglarized door openings had lower mean of occupant surveillability (n = 46, M = 7.20, SD = 7.78) than non-burglarized door openings (n = 602, M = 7.87, SD = 6.93). Range of visible sightlines for burglarized and non-burglarized door openings was almost identical.

Road surveillability of door openings ranged from 0 to 32, with a mean of 7.66 (n = 648, SD = 7.52). Burglarized door openings had higher mean of road surveillability (n = 46, M = 9.15, SD = 8.88) than non-burglarized door openings (n = 602, M = 7.55, SD = 7.40). Range of visible sightlines for burglarized and non-burglarized door openings was almost identical.

Pedestrian surveillability of door openings ranged from 0 to 132, with a mean of 36.89 (n = 648, SD = 35.87). Burglarized door openings had higher mean of pedestrian surveillability (n = 46, M = 42.07, SD = 41.16) than non-burglarized door openings (n = 602, M = 36.50, SD = 35.44). Range of visible sightlines for burglarized and non-burglarized door openings was almost identical.

Window openings. Occupant surveillability of window openings ranged from 0 to 36, with a mean of 8.86 (n = 2531, SD = 6.72). Burglarized window openings had lower mean of occupant surveillability (n = 19, M = 7.37, SD = 5.84) than non-burglarized window openings (n = 2512, M = 8.87, SD = 6.73). In addition, the number of visible sightlines to burglarized window openings ranged from 0 and 23, while that number ranged from 0 and 35 for non-burglarized window openings.

Road surveillability of window openings ranged from 0 to 33, with a mean of 7.82 (n = 2531, SD = 7.68). Burglarized window openings had lower mean of road surveillability (n = 19, M = 7.11, SD = 7.67) than non-burglarized window openings (n = 2512, M = 7.82, SD = 7.68). In addition, the number of visible sightlines to burglarized window openings ranged from 0 and 25, while that number ranged from 0 and 33 for non-burglarized window openings.

Pedestrian surveillability of window openings ranged from 0 to 139, with a mean of 37.48 (n = 2531, SD = 34.29). Burglarized window openings had lower mean of pedestrian surveillability (n = 19, M = 33.89, SD = 30.45) than non-burglarized window openings (n = 2512, M = 37.50, SD = 34.32). In addition, the number of visible sightlines to burglarized window openings ranged from 0 and 113, while that number ranged from 0 and 139 for non-burglarized window openings.

In summary, burglarized building openings, door openings and window openings had lower degrees of occupant surveillability compared to non-burglarized ones. In addition, burglarized building openings and door openings had higher degrees of road and pedestrian surveillability compared to non-burglarized ones. Burglarized window openings had lower degrees of road and pedestrian surveillability compared to non-burglarized ones.

Table 44

Descriptive statistics for occupant, road and pedestrian surveillability within 141 feet of building openings (Source: Author).

	141 feet											
Independent Variables	N	Mean	Mode	SD	Min	Max						
Occupant surveillability	3179	8.65	0	6.79	0	36						
Road surveillability	3179	7.78	0	7.65	0	33						
Pedestrian surveillability	3179	37.36	0	34.61	0	139						
Occupant surveillability (Door)	648	7.83	0	6.99	0	35						
Road surveillability (Door)	648	7.66	0	7.52	0	32						
Pedestrian surveillability (Door)	648	36.89	0	35.87	0	132						
Occupant surveillability (Window)	2531	8.86	0, 5	6.72	0	36						
Road surveillability (Window)	2531	7.82	0	7.68	0	33						
Pedestrian surveillability (Window)	2531	37.48	0	34.29	0	139						
	141 feet burglarized						141 feet not burglarized					
Independent Variables	N	Mean	Mode	SD	Min	Max	N	Mean	Mode	SD	Min	Max
Occupant surveillability	65	7.25	0	7.23	0	34	3114	8.68	0	6.78	0	36
Road surveillability	65	8.55	0	8.53	0	29	3114	7.77	0	7.63	0	33
Pedestrian surveillability	65	39.68	0	38.29	0	130	3114	37.31	0	34.54	0	139
Occupant surveillability (Door)	46	7.20	0	7.78	0	34	602	7.87	0	6.93	0	35
Road surveillability (Door)	46	9.15	0	8.88	0	29	602	7.55	0	7.40	0	32
Pedestrian surveillability (Door)	46	42.07	0	41.16	0	130	602	36.50	0	35.44	0	132
Occupant surveillability (Window)	19	7.37	0,7	5.84	0	23	2512	8.87	5	6.73	0	36
Road surveillability (Window)	19	7.11	4	7.67	0	25	2512	7.82	0	7.68	0	33
Pedestrian surveillability (Window)	19	33.89	8,42	30.45	2	113	2512	37.50	0	34.32	0	139

5.3.2 Inferential statistics

Inferential statistics used in this study are Spearman's rank correlation, Mann-Whitney U and binary logistic regression. Non-parametric tests and techniques robust to violations of normality are used because; (a) the distributions of occupant, road and pedestrian surveillability are positively skewed, with most of the scores on the lowest range (i.e. zero in this study), and (b) the results of the Kolmogorov-Smirnov tests showed that the distributions of our independent variables are not normal.

5.3.2.1 Spearman's rank correlation

Spearman's rank correlation was performed to determine the relationship between the degree of occupant, road and pedestrian surveillability and burglary commissions within 49, 95 and 141 feet of all building openings, door openings and window openings. Statistics are presented according to distance measures and opening type (See Table 45).

5.3.2.1.1 Within 49 feet distance

All building openings. The results of Spearman's correlation analysis revealed a significant weak negative correlation between occupant surveillability and burglary commissions ($r = -0.07$, $p < 0.001$). Further, insignificant direct relationships were observed between road ($r = 0.03$, $p > 0.05$) or pedestrian ($r = 0.03$, $p > 0.05$) surveillability and burglary commission.

Door openings. The results of Spearman's correlation analysis revealed a significant weak positive correlation between road surveillability and burglary commissions ($r = 0.09$, $p = 0.02$). Further, an insignificant direct relationship was observed between pedestrian ($r = 0.03$, $p >$

0.05) surveillability and burglary commissions, in addition to an insignificant inverse relationship between occupant (r = -0.04, $p > 0.05$) or and burglary commissions.

Window openings. The results of Spearman's correlation analysis revealed a significant weak negative correlation between occupant surveillability and burglary commissions (r = − 0.05, $p = 0.008$). Further, insignificant direct relationships were observed between road (r = 0.002, $p > 0.05$) or pedestrian (r = 0.02, $p > 0.05$) surveillability and burglary commissions at this distance.

5.3.2.1.2 Within 95 feet distance

All building openings. The results of Spearman's correlation analysis revealed a significant weak negative correlation between occupant surveillability and burglary commissions (r = − 0.05, $p = 0.005$). Further, insignificant direct relationships were observed between road (r = 0.01, $p > 0.05$) or pedestrian (r = 0.01, $p > 0.05$) surveillability and burglary commissions.

Door openings. According to Spearman's correlation analysis, no significant relationship was observed between occupant (r = 0.01, $p > 0.05$), road (r = 0.05, $p > 0.05$) or pedestrian (r = 0.02, $p > 0.05$) surveillability and burglary commissions. Those relationships are all direct.

Window openings. The results of Spearman's correlation analysis revealed a significant weak negative correlation between occupant surveillability and burglary commissions (r = − 0.04, $p = 0.03$). Further, inverse significant relationships were observed between road (r = -0.02, $p > 0.05$) or pedestrian (r = -0.004, $p > 0.05$) surveillability and burglary commissions at this distance.

5.3.2.1.3 Within 141 feet distance

All building openings. The results of Spearman's correlation analysis revealed a significant weak negative correlation between occupant surveillability and burglary commissions ($r = -0.04$, $p = 0.03$). Further, insignificant direct relationships were observed between road ($r = 0.01$, $p > 0.05$) or pedestrian ($r = 0.002$, $p > 0.05$) surveillability and burglary commissions.

Door openings. According to Spearman's correlation analysis, no significant relationship was observed between occupant ($r = -0.04$, $p > 0.05$), road ($r = 0.04$, $p > 0.05$) or pedestrian ($r = 0.03$, $p > 0.05$) surveillability and burglary commissions. That relationship between occupant surveillability and burglary commissions is inverse and the relationships between road and pedestrian surveillability and burglary commissions are direct.

Window openings. Lastly, according to Spearman's correlation analysis, no significant relationship was observed between occupant ($r = -0.02$, $p > 0.05$), road ($r = -0.01$, $p > 0.05$) or pedestrian ($r = -0.004$, $p > 0.05$) surveillability and burglary commissions. Those relationships are all inverse.

5.3.2.1.4 Spearman's rank correlation in summary

I conducted Spearman's rank correlation to determine the relationship between the degree of occupant, road and pedestrian surveillability and burglary commissions (See Table 45). The following hypothesis was proposed in the introductory chapter of this dissertation:

- There is a statistically significant inverse relationship between the degree of occupant, road and pedestrian surveillability and commission of residential burglaries.

For all building openings (i.e. doors and windows), occupant surveillability within 49, 95 and 141 feet distance of building openings correlated significantly inverse with burglary commissions. As one moves away from building openings (i.e. from 49 feet to 95 feet and to 141 feet), the level of significance and the coefficient decrease. Nevertheless, the relationship between road or pedestrian surveillability and burglary commissions were direct but insignificant at all distance measures of surveillability.

For door openings, the relationship between road surveillability and burglary commissions found to be statically significant and direct within 49 feet distance of door openings. That direct relationship lost its significance within 95 and 141 feet distance of door openings. The relationship between pedestrian surveillability and burglary commission through doors was positive and insignificant at all three distance measures of surveillability. Lastly, the relationship between occupant surveillability and burglary commissions through door was statistically insignificant and ambiguous. This relationship is shown to be inverse within 49 and 141 feet of door openings but was direct within 95 feet distance of doors.

For window openings, occupant surveillability within 49 and 95 feet distance of windows openings correlated significantly inverse with burglary commissions. That relationship remained negative but lost its significance within 141 feet distance of window openings. In addition, the relationship between road or pedestrian surveillability and burglary commissions was statistically insignificant and ambiguous. Those relationships are shown to be direct within 49 feet of window openings but become inverse within 95 and 141 feet distance of windows.

Table 45

Spearman's rank correlation for the relationship between burglary commissions and occupant, road and pedestrian surveillability (Source: Author).

	49 feet		95 feet		141 feet	
Independent Variables	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.
Occupant surveillability	-0.07	0.000	-0.05	0.005	-0.04	0.027
Road surveillability	0.03	0.083	0.01	0.630	0.01	0.642
Pedestrian surveillability	0.03	0.122	0.01	0.774	0.00	0.895
Occupant surveillability (Door)	-0.04	0.373	0.01	0.856	-0.04	0.274
Road surveillability (Door)	0.09	0.020	0.05	0.241	0.04	0.303
Pedestrian surveillability (Door)	0.03	0.435	0.02	0.549	0.03	0.521
Occupant surveillability (Window)	-0.05	0.008	-0.04	0.028	-0.02	0.397
Road surveillability (Window)	0.00	0.932	-0.02	0.386	-0.01	0.707
Pedestrian surveillability (Window)	0.02	0.274	0.00	0.844	0.00	0.843

Note: Burglarized building openings were codes as 1, and non-burglarized building openings as 0. Coefficients show the relationship between visibility measures and the dichotomous variable of burglary commission.

5.3.2.2 Mann-Whitney U test

Mann-Whitney U test was performed to determine whether the degree of occupant, road and pedestrian surveillability differ between burglarized and non-burglarized building openings, door openings and window openings. Statistics are presented according to distance measures and opening type (See Table 46 through Table 49).

5.3.2.2.1 Within 49 feet distance

All building openings. The results of Mann-Whitney U test showed that burglarized building openings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized building openings (U = 73124.00, Z = -3.95, $p < 0.001$). No statistically significant difference was observed between the mean rank of road (U = 93120.50, Z = -1.74, $p > 0.05$) or pedestrian (U = 91093.00, Z = -1.55, $p > 0.05$) surveillability for burglarized and non-burglarized building openings. However, burglarized building openings had higher mean rank of road and pedestrian surveillability compared to non-burglarized building openings.

Door openings. The results of Mann-Whitney U test showed that burglarized door openings had statistically significant higher mean rank of road surveillability compared to non-burglarized door openings (U = 12058.00, Z = -2.32, $p = 0.02$). No statistically significant difference was observed between the mean rank of occupant (U = 12836.50.00, Z = -0.89, $p > 0.05$) or pedestrian (U = 12977.00, Z = -0.78, $p > 0.05$) surveillability for burglarized and non-burglarized door openings. However, burglarized door openings had lower mean rank of occupant surveillability and higher mean rank of road surveillability compared to non-burglarized door openings.

Window openings. The results of Mann-Whitney U test showed that burglarized window openings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized building openings (U = 15634.50, Z = -2.65, $p = 0.008$). No statistically significant difference was observed between the mean rank of road (U = 23692.00, Z = -0.09, $p > 0.05$) or pedestrian (U = 20781.00, Z = -1.09, $p > 0.05$) surveillability for burglarized and non-burglarized window openings. However, burglarized window openings had higher mean rank of road and pedestrian surveillability compared to non-burglarized window openings.

In summary, burglarized building openings and window openings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized building openings or window openings. In addition, burglarized door openings had statistically significant higher mean rank of road surveillability compared to non-burglarized ones. The other mean differences were not statistically significant, but in general burglarized building openings, door openings and window openings had lower mean rank of occupant surveillability and higher mean rank of road and pedestrian surveillability compared to non-burglarized ones.

Table 46

Mann-Whitney U test for mean differences between occupant, road and pedestrian surveillability for burglarized and non-burglarized building openings, door openings and window openings within 49 feet of building openings (Source: Author).

Independent Variables	Z	Sig.	Mann-Whitney U	Not Burglarized Mean Rank	Burglarized Mean Rank
Occupant surveillability 49 feet	-3.95	0.000	73124.00	1599.02	1157.98
Road surveillability 49 feet	-1.74	0.083	93120.50	1587.40	1714.38
Pedestrian surveillability 49 feet	-1.55	0.122	91093.00	1586.75	1745.57
Occupant surveillability 49 feet (Door)	-0.89	0.373	12836.50	326.18	302.55
Road surveillability 49 feet (Door)	-2.32	0.021	12058.00	321.53	363.37
Pedestrian surveillability 49 feet (Door)	-0.78	0.435	12977.00	323.06	343.39
Occupant surveillability 49 feet (Windows)	-2.65	0.008	15634.50	1269.28	832.87
Road surveillability 49 feet (Windows)	-0.09	0.932	23692.00	1265.93	1275.05
Pedestrian surveillability 49 feet (Windows)	-1.09	0.274	20781.00	1264.77	1428.26

5.3.2.2.2 Within 95 feet distance

All building openings. The results of Mann-Whitney U test showed that burglarized building openings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized building openings (U = 80674.00, Z = -2.83, $p = 0.005$). No statistically significant difference was observed between the mean rank of road (U = 97699.00, Z = -0.48, $p > 0.05$) or pedestrian (U = 99100.50, Z = -0.29, $p > 0.05$) surveillability for burglarized and non-burglarized building openings. However, burglarized building openings had higher mean rank of road and pedestrian surveillability compared to non-burglarized building openings.

Door openings. According to Mann-Whitney U test no statistically significant difference was observed between the mean rank of occupant (U = 13630.50, Z = -0.18, $p > 0.05$), road (U = 12426.50, Z = -1.17, $p > 0.05$) or pedestrian (U = 13114.50, Z = -0.60, $p > 0.05$) surveillability for burglarized and non-burglarized door openings. Burglarized door openings had higher mean rank of occupant, road and pedestrian surveillability compared to non-burglarized door openings.

Window openings. The results of Mann-Whitney U test showed that burglarized window openings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized window openings (U = 16945.00, Z = -2.20, $p = 0.03$). No statistically significant difference was observed between the mean rank of road (U = 21132.50, Z = -0.87, $p > 0.05$) or pedestrian (U = 23241.00, Z = -0.20, $p > 0.05$) surveillability for burglarized and non-burglarized window openings. However, burglarized window openings had lower mean rank of road and pedestrian surveillability compared to non-burglarized window openings.

In summary, burglarized building openings and window openings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized building openings or window openings. The other mean differences were not statistically significant, but ambiguities are observed. For instance, burglarized door openings had higher mean rank of occupant surveillability compared to non-burglarized door openings. Also, burglarized building openings and door openings had higher mean rank of road and pedestrian surveillability compared to non-burglarized ones. But burglarized window openings had lower mean rank of road and pedestrian surveillability compared to non-burglarized windows.

Table 47

Mann-Whitney U test for mean differences between occupant, road and pedestrian surveillability for burglarized and non-burglarized building openings, door openings and window openings within 95 feet of building openings (Source: Author).

Independent Variables	Z	Sig.	Mann-Whitney U	Not Burglarized Mean Rank	Burglarized Mean Rank
Occupant surveillability 95 feet	-2.83	0.005	80674.00	1596.59	1274.14
Road surveillability 95 feet	-0.48	0.630	97699.00	1588.87	1643.94
Pedestrian surveillability 95 feet	-0.29	0.774	99100.50	1589.32	1622.38
Occupant surveillability 95 feet (Door)	-0.18	0.856	13630.50	324.14	329.18
Road surveillability 95 feet (Door)	-1.17	0.240	12426.50	322.14	355.36
Pedestrian surveillability 95 feet (Door)	-0.60	0.548	13114.50	323.28	340.40
Occupant surveillability 95 feet (Windows)	-2.20	0.028	16945.00	1268.75	901.84
Road surveillability 95 feet (Windows)	-0.87	0.386	21132.50	1267.09	1122.24
Pedestrian surveillability 95 feet (Windows)	-0.20	0.844	23241.00	1266.25	1233.21

5.3.2.2.3 Within 141 feet distance

All building openings. The results of Mann-Whitney U test showed that burglarized building openings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized building openings (U = 85033.50, Z = -2.21, $p = 0.03$). No statistically significant difference was observed between the mean rank of road (U = 97805.00, Z = -0.47, $p > 0.05$) or pedestrian (U = 100240.50, Z = -0.13, $p > 0.05$) surveillability for burglarized and non-burglarized building openings. However, burglarized building openings had higher mean rank of road and pedestrian surveillability compared to non-burglarized building openings.

Door openings. According to Mann-Whitney U test, the mean rank of occupant (U = 12509.50, Z = -1.09, $p > 0.05$), road (U = 12591.50, Z = -1.03, $p > 0.05$) or pedestrian (U = 13062.00, Z = -0.64, $p > 0.05$) surveillability were not significantly different for burglarized and non-burglarized door openings. However, burglarized door openings had lower mean rank of occupant surveillability and higher mean rank of road and pedestrian surveillability compared to non-burglarized door openings.

Window openings. According to Mann-Whitney U test, no significant difference was found between the mean rank of occupant (U = 21179.50, Z = -0.85, $p > 0.05$), road (U = 22673.50, Z = -0.38, $p > 0.05$) or pedestrian (U = 23234.50, Z = -0.20, $p > 0.05$) surveillability for burglarized and non-burglarized window openings. However, burglarized window openings had lower mean rank of occupant, road and pedestrian surveillability compared to non-burglarized window openings.

In summary, burglarized building openings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized building openings. The other mean differences were not statistically significant. However, burglarized door openings and window openings had lower mean rank of occupant surveillability compared to non-burglarized ones. Some ambiguities are observed, for instance burglarized building openings and door openings had higher mean rank of road and pedestrian surveillability compared to non-burglarized one. But, burglarized window openings had lower mean rank of road and pedestrian surveillability compared to non-burglarized windows.

Table 48

Mann-Whitney U test for mean differences between occupant, road and pedestrian surveillability for burglarized and non-burglarized building openings, door openings and window openings within 141 feet of building openings (Source: Author).

Independent Variables	Z	Sig.	Mann-Whitney U	Not Burglarized Mean Rank	Burglarized Mean Rank
Occupant surveillability 141 feet	-2.21	0.027	85033.50	1595.19	1341.21
Road surveillability 141 feet	-0.47	0.641	97805.00	1588.91	1642.31
Pedestrian surveillability 141 feet	-0.13	0.895	100240.50	1589.69	1604.84
Occupant surveillability 141 feet (Door)	-1.09	0.274	12509.50	326.72	295.45
Road surveillability 141 feet (Door)	-1.03	0.302	12591.50	322.42	351.77
Pedestrian surveillability 141 feet (Door)	-0.64	0.521	13062.00	323.20	341.54
Occupant surveillability 141 feet (Windows)	-0.85	0.397	21179.50	1267.07	1124.71
Road surveillability 141 feet (Windows)	-0.38	0.707	22673.50	1266.47	1203.34
Pedestrian surveillability 141 feet (Windows)	-0.20	0.843	23234.50	1266.25	1232.87

5.3.2.2.4 Mann-Whitney U test in summary

I conducted Mann-Whitney U test to determine whether the degree of occupant, road and pedestrian surveillability differ between burglarized and non-burglarized building openings, door openings and window openings (See Table 46 through Table 49). The following hypothesis was proposed in the introductory chapter of this dissertation:

- Burglarized building openings have statistically significant lower mean of occupant, road and pedestrian surveillability compared to non-burglarized building openings.

The results revealed that burglarized building openings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized building openings within all three distance measures of surveillability. The mean rank of road and pedestrian surveillability was not statistically different for burglarized and non-burglarized building openings at any distance. Nevertheless, burglarized building openings had higher mean rank of road and pedestrian surveillability compared to non-burglarized building openings.

Burglarized door openings had higher mean rank of road surveillability compared to non-burglarized door openings within all distance measure of surveillability. Only the mean difference within 49 feet of door openings was statistically significant. The mean rank of occupant and pedestrian surveillability was not statistically different for burglarized and non-burglarized door openings at any distance. Burglarized door openings had higher mean rank of pedestrian surveillability compared to non-burglarized door openings. The mean differences of occupant surveillability measures were ambiguous. Burglarized door openings had lower mean rank of occupant surveillability compared to non-burglarized door openings within 49 and 141 feet of door openings, but had higher mean rank of occupant surveillability compared to non-burglarized door openings within 95 feet distance of door openings.

Burglarized window openings had lower mean rank of occupant surveillability compared to non-burglarized window openings within all distance measure of surveillability. Only the mean difference within 49 feet of window openings was statistically significant. The mean rank of road and pedestrian surveillability were insignificant and ambiguous. Burglarized window openings had higher mean rank of road and pedestrian surveillability compared to non-burglarized door openings within 49 and 95 feet of door openings, but had lower mean rank of road and pedestrian surveillability compared to non-burglarized door openings within 141 feet distance of window openings.

Table 49

Mann-Whitney U test for mean differences between occupant, road and pedestrian surveillability for burglarized and non-burglarized building openings, door openings and window openings within 49, 95 and 141 feet of building openings (Source: Author).

	49 feet		95 feet		141 feet	
Independent Variables	Mann-Whitney	Sig.	Mann-Whitney	Sig.	Mann-Whitney	Sig.
Occupant surveillability	73124.00	0.000	80674.00	0.005	85033.50	0.027
Road surveillability	93120.50	0.083	97699.00	0.630	97805.00	0.641
Pedestrian surveillability	91093.00	0.122	99100.50	0.774	100240.50	0.895
Occupant surveillability (Door)	12836.50	0.373	13630.50	0.856	12509.50	0.274
Road surveillability (Door)	12058.00	0.021	12426.50	0.240	12591.50	0.302
Pedestrian surveillability (Door)	12977.00	0.435	13114.50	0.548	13062.00	0.521
Occupant surveillability (Window)	15634.50	0.008	16945.00	0.028	21179.50	0.397
Road surveillability (Window)	23692.00	0.932	21132.50	0.386	22673.50	0.707
Pedestrian surveillability (Window)	20781.00	0.274	23241.00	0.844	23234.50	0.843

5.3.2.3 Binary Logistic Regression

Binary logistic regression was conducted to make predictions regarding the most likely entry points of burglaries from knowledge of occupant, road and pedestrian surveillability within 49, 95 and 141 feet distance of building openings, door openings and window openings. In addition, performance of the binary logistic models was assessed through receiver operating characteristic (ROC) curves. The area under of the ROC curve shows accuracy or performance of logistic regression. Models are less accurate when curves are closer to the 45-degree baseline. In addition, models are not accurate when curves intersect the 45-degree diagonal line.

5.3.2.3.1 Within 49 feet distance

All building openings. First, a logistic regression analysis was conducted to understand whether burglary commissions can be reliably predicted from knowledge of occupant surveillability (See Table 50). The test of the full model against the constant only model was statistically significant (χ^2 (1) = 14.95, $p < 0.001$). The Hosmer-Lemeshow test (χ^2 (5) = 5.88, $p >$ 0.05) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value of 0.03 indicated that the model was not accurate in predicting burglary commissions.

According to the model, burglary commission was associated with lower degrees of occupant surveillability (OR = 0.79; 95%CI = 0.68-0.90; p = 0.001). The odds ratio of 0.79 shows that burglary commission is 0.79 times as likely (or about 21% less likely) with a one unit increase in occupant surveillability. In addition, the log of the odds of burglary commission was negatively related to occupant surveillability. In fact, for every one unit increase in occupant surveillability, the log odds of burglary commission decreased by 0.24. In other words, the more a building opening was surveyed by neighboring building openings, the less likely it was that that building opening would be chosen for burglary commission.

Model 2 includes eight additional theoretically important variables: building use, territoriality, diversity, maintenance, vacant lot, corner/middle lot, no-trespassing symbols and facing of building openings. The test of the full model against the constant only model was statistically significant (χ^2 (11) = 39.37, $p < 0.001$). According to the likelihood ratio test statistic, Model 2 was superior to Model 1 in terms of overall model fit. The H-L test (χ^2 (8) = 12.12, $p > 0.05$) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value of 0.07 indicated that the model was not accurate in predicting burglary commissions.

According to the model, burglary commission was associated with lower degrees of occupant surveillability (OR = 0.83; 95%CI = 0.71-0.98; $p < 0.05$). The odds ratio of 0.83 shows that burglary commission is 0.83 times as likely (or about 17% less likely) with a one unit increase in occupant surveillability, holding all other independent variables constant. In addition, the log of the odds of burglary commission was negatively related to occupant surveillability. In fact, for every one unit increase in occupant surveillability, the log odds of burglary commission decreased by 0.18.

Next, a logistic regression analysis was performed to understand whether burglary commissions can be reliably predicted from knowledge of road surveillability (See Table 51). The test of the full model against the constant only model was statistically insignificant (χ^2 (1) = 3.78, $p = 0.052$). Even though the model did not reach statistical significance, burglary commission was associated with higher degrees of road surveillability (OR = 1.17; 95%CI =

1.01-1.34; $p = 0.03$). Therefore, I cautiously report that the odds ratio of 1.17 shows that burglary commission is 1.17 times as likely (or about 17% more likely) with a one unit increase in road surveillability. In addition, the log of the odds of a burglary commission was positively related to road surveillability. In fact, for every one unit increase in road surveillability, the log odds of burglary commission increased by 0.15. In other words, the more a building opening was surveyed from road, the more likely it was that that building opening would be chosen for burglary commission.

Then, a logistic regression analysis was employed to understand whether burglary commissions can be reliably predicted from knowledge of pedestrian surveillability (See Table 52). The test of the full model against the constant only model was statistically insignificant (χ^2 (1) = 2.62, $p > 0.05$).

Lastly, the area under the ROC curve for prediction of burglary commission in relation to occupant surveillability gave a value of 0.36 (95%CI = 0.30-0.43; $p < 0.001$). This value showed that occupant surveillability is negatively associated with burglary commissions, but the model is not accurate in classifying true positive events. The area under the ROC curve for prediction of burglary commission in relation to road and pedestrian surveillability gave values of 0.54 (95%CI = 0.47-0.61; $p > 0.05$) and 0.55 (95%CI = 0.48-0.62; $p > 0.05$) respectively. These values showed that the road and pedestrian surveillability models are neither significant nor accurate at classifying true positive events (See Table 53 and Figure 71).

Table 50

Logistic regression analysis of 3179 building openings for burglary commissions in relation to occupant surveillability within 49 feet of building openings (Source: Author).

							95% C.I. for Exp(B)	
Independent and Control Variables	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Occupant surveillability 49 feet	-0.24	0.07	11.38	1	0.001	0.79	0.68	0.90
Constant	-3.47	0.15	526.54	1	0.000	0.03		
Model 2								
Occupant surveillability 49 feet	-0.18	0.08	4.89	1	0.027	0.83	0.71	0.98
Building Use (1 = 2 plus units)	0.39	0.27	2.06	1	0.152	1.47	0.87	2.51
Territoriality (1 = Completely fenced)	-0.98	0.30	10.61	1	0.001	0.37	0.21	0.68
Presence of facilities within 49 feet (1 = Yes)	0.07	0.76	0.01	1	0.930	1.07	0.24	4.76
Adjacent vacant lot (1 = Yes)	0.65	0.43	2.29	1	0.131	1.92	0.82	4.47
Maintenance (1 = Maintained)	-0.01	0.25	0.00	1	0.978	0.99	0.60	1.64
Corner vs. middle lot (1 = Corner lot)	0.31	0.29	1.18	1	0.278	1.37	0.78	2.41
Presence of no-trespassing signs (1 = Yes)	0.23	0.34	0.46	1	0.499	1.26	0.64	2.47
Opening face (1 = Alley)	0.34	0.37	0.84	1	0.359	1.40	0.68	2.87
Opening face (1 = Regional)	-0.08	0.37	0.05	1	0.822	0.92	0.44	1.91
Opening face (1 = Neighborhood collector)	0.75	0.50	2.22	1	0.136	2.12	0.79	5.68
Constant	-3.63	0.38	89.10	1	0.000	0.03		

Model Evaluation	Block1	df	Sig.	Block2	df	Sig.
Chi-square	14.95	1	0.000	39.37	11	0.000
-2 Log likelihood	619.41			594.99		
Cox and Snell (R square)	0.005			0.012		
Nagelkerke (R Square)	0.026			0.068		
Hosmer and Lemeshow Test (Chi-square)	5.88	5	0.318	12.12	8	0.146

Table 51

Logistic regression analysis of 3179 building openings for burglary commissions in relation to road surveillability within 49 feet of building openings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B)	
							Lower	Upper
Model 1								
Road surveillability 49 feet	0.15	0.07	4.54	1	0.033	1.17	1.01	1.34
Constant	-3.96	0.14	825.61	1	0.000	0.02		

Model Evaluation	Block1	df	Sig.
Chi-square	3.78	1	0.052
-2 Log likelihood	630.58		
Cox and Snell (R square)	0.001		
Nagelkerke (R Square)	0.007		
Hosmer and Lemeshow Test (Chi-square)	0.20	1	0.652

Table 52

Logistic regression analysis of 3179 building openings for burglary commissions in relation to pedestrian surveillability within 49 feet of building openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Pedestrian surveillability 49 feet	0.03	0.02	2.80	1	0.094	1.03	0.99	1.07
Constant	-4.02	0.16	631.53	1	0.000	0.02		

Model Evaluation	Block1	df	Sig.
Chi-square	2.62	1	0.105
-2 Log likelihood	631.73		
Cox and Snell (R square)	0.001		
Nagelkerke (R Square)	0.005		
Hosmer and Lemeshow Test (Chi-square)	6.35	3	0.096

Table 53

ROC statistics for burglary commissions in relation to occupant, road and pedestrian surveillability within 49 feet distance of building openings (Source: Author).

Independent Variables	Area	S.E.	Sig.	95% C.I. Lower	95% C.I. Upper
Occupant surveillability 49 feet	0.36	0.03	0.000	0.30	0.43
Road surveillability 49 feet	0.54	0.04	0.270	0.47	0.61
Pedestrian surveillability 49 feet	0.55	0.04	0.167	0.48	0.62

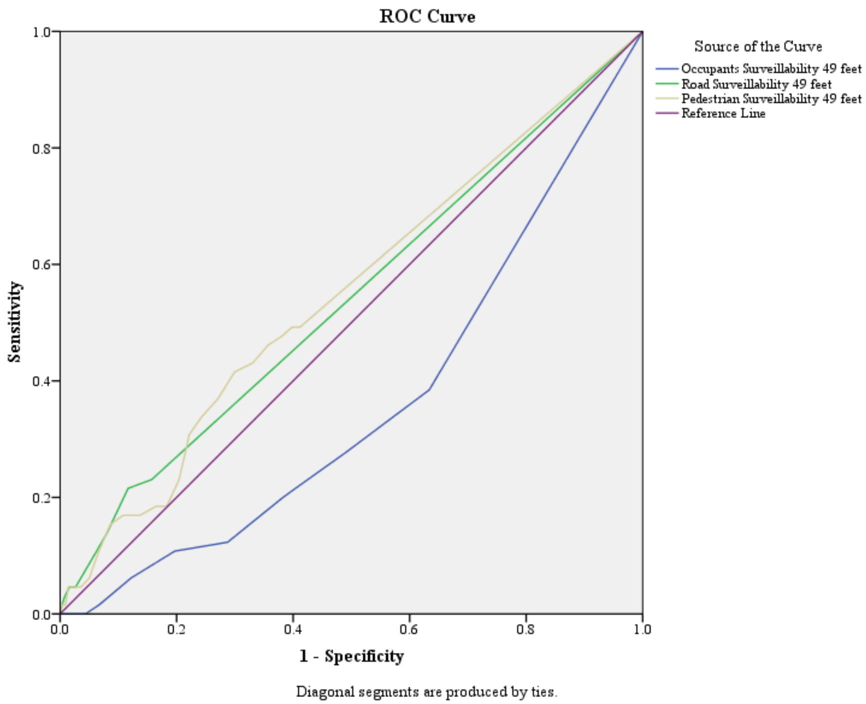


Figure 71. ROC curves for burglary commissions in relation to occupant, road and pedestrian surveillability within 49 feet of building openings (Source: Author).

Door openings. A logistic regression analysis was conducted to understand whether burglary commission through doors can be reliably predicted from knowledge of occupant surveillability (See Table 54). The test of the full model against the constant only model was statistically insignificant (χ^2 (1) = 0.16, $p > 0.05$).

Next, a logistic regression analysis was performed to understand whether burglary commission through doors can be reliably predicted from knowledge of road surveillability (See Table 55). The test of the full model against the constant only model was statistically significant (χ^2 (1) = 7.66, $p = 0.006$). The Hosmer-Lemeshow test (χ^2 (1) = 0.39, $p > 0.05$) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value of 0.03 indicated that the model was not accurate in predicting burglary commission through door openings.

According to the model, burglary commission through doors was associated with higher degrees of road surveillability (OR = 1.35; 95%CI = 1.11-1.64; $p = 0.001$). The odds ratio of 1.35 shows that burglary commission through doors is 1.35 times as likely (or about 35% more likely) with a one unit increase in road surveillability. In addition, the log of the odds of burglary commission through doors was positively related to road surveillability. In fact, for every one unit increase in road surveillability, the log odds of burglary commission through doors increased by 0.30. In other words, the more a door was surveyed from roads, the more likely it was that that door would be chosen for burglary commission.

Model 2 includes eight additional theoretically important variables: building use, territoriality, diversity, maintenance, vacant lot, corner/middle lot, no-trespassing symbols and facing of building openings. The test of the full model against the constant only model was statistically insignificant (χ^2 (11) = 19.49, p = 0.053). Even though the model did not reach statistical significance, burglary commission through doors was associated with higher degrees of road surveillability (OR = 1.27; 95%CI = 1.01-1.59; p = 0.04). Therefore, I cautiously report that the odds ratio of 1.27 shows that burglary commission through doors is 1.27 times as likely (or about 27% more likely) with a one unit increase in road surveillability. In addition, the log of the odds of burglary commission through doors was positively related to road surveillability. In fact, for every one unit increase in road surveillability, the log odds of burglary commission through doors increased by 0.24.

Then, a logistic regression analysis was employed to understand whether burglary commission through doors can be reliably predicted from knowledge of pedestrian surveillability (See Table 56). The test of the full model against the constant only model was statistically insignificant (χ^2 (1) = 1.01, $p > 0.05$).

Lastly, the area under the ROC curve for prediction of burglary commission through doors in relation to occupant, roads and pedestrian surveillability gave values of 0.46 (95%CI = 0.37-0.55; $p > 0.05$), 0.56 (95%CI = 0.47-0.66; $p > 0.05$) and 0.53 (95%CI = 0.44-0.62; $p > 0.05$) respectively. These values showed that the occupant, road and pedestrian surveillability models are neither significant nor accurate at classifying true positive events (See Figure 72 and Table 57).

Table 54

Logistic regression analysis of 648 doors for burglary commissions in relation to occupant surveillability within 49 feet of door openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Occupant surveillability 49 feet (Doors)	-0.03	0.08	0.16	1	0.690	0.97	0.82	1.14
Constant	-2.53	0.18	192.89	1	0.000	0.08		

Model Evaluation	Block1	df	Sig.
Chi-square	0.16	1	0.685
-2 Log likelihood	331.85		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.001		
Hosmer and Lemeshow Test (Chi-square)	5.36	3	0.147

Table 55

Logistic regression analysis of 648 doors for burglary commissions in relation to road surveillability within 49 feet distance of door openings (Source: Author).

							95% C.I. for Exp(B)	
Independent and Control Variables	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Road surveillability 49 feet (Doors)	0.30	0.10	9.39	1	0.002	1.35	1.11	1.64
Constant	-2.73	0.17	257.58	1	0.000	0.07		
Model 2								
Road surveillability 49 feet (Doors)	0.24	0.12	4.28	1	0.039	1.27	1.01	1.59
Building Use (1 = 2 plus units)	0.12	0.35	0.11	1	0.738	1.12	0.57	2.24
Territoriality (1 = Completely fenced)	-0.78	0.38	4.26	1	0.039	0.46	0.22	0.96
Presence of facilities within 49 feet (1 = Yes)	0.57	0.85	0.45	1	0.501	1.77	0.34	9.31
Adjacent vacant lot (1 = Yes)	0.77	0.54	2.04	1	0.154	2.17	0.75	6.27
Maintenance (1 = Maintained)	-0.03	0.32	0.01	1	0.931	0.97	0.52	1.82
Corner vs. middle lot (1 = Corner lot)	0.37	0.38	0.94	1	0.333	1.44	0.69	3.03
Presence of no-trespassing signs (1 = Yes)	-0.04	0.45	0.01	1	0.936	0.96	0.40	2.34
Opening face (1 = Alley)	-0.13	0.46	0.08	1	0.779	0.88	0.36	2.16
Opening face (1 = Regional)	-0.24	0.42	0.32	1	0.571	0.79	0.35	1.79
Opening face (1 = Neighborhood collector)	0.42	0.58	0.51	1	0.475	1.51	0.49	4.73
Constant	-2.55	0.45	32.33	1	0.000	0.08		
Model Evaluation	Block1	df	Sig.		Block2	df	Sig.	
Chi-square	7.66	1	0.006		19.49	11	0.053	
-2 Log likelihood	324.36				312.53			
Cox and Snell (R square)	0.012				0.030			
Nagelkerke (R Square)	0.029				0.074			
Hosmer and Lemeshow Test (Chi-square)	0.39	1	0.531		16.99	8	0.030	

Table 56

Logistic regression analysis of 648 doors for burglary commissions in relation to pedestrian surveillability within 49 feet of door openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Pedestrian surveillability 49 feet (Doors)	0.03	0.03	1.04	1	0.307	1.03	0.98	1.08
Constant	-2.69	0.20	182.23	1	0.000	0.07		

Model Evaluation	Block1	df	Sig.
Chi-square	1.01	1	0.315
-2 Log likelihood	331.01		
Cox and Snell (R square)	0.002		
Nagelkerke (R Square)	0.004		
Hosmer and Lemeshow Test (Chi-square)	1.87	4	0.760

Table 57

ROC statistics for burglary commissions in relation to occupant, road and pedestrian surveillability models within 49 feet of door openings (Source: Author).

				95% C.I.	
Independent Variables	Area	S.E.	Sig.	Lower	Upper
Occupant surveillability 49 feet (Doors)	0.46	0.05	0.409	0.37	0.55
Road surveillability 49 feet (Doors)	0.56	0.05	0.144	0.47	0.66
Pedestrian surveillability 49 feet (Doors)	0.53	0.05	0.478	0.44	0.62

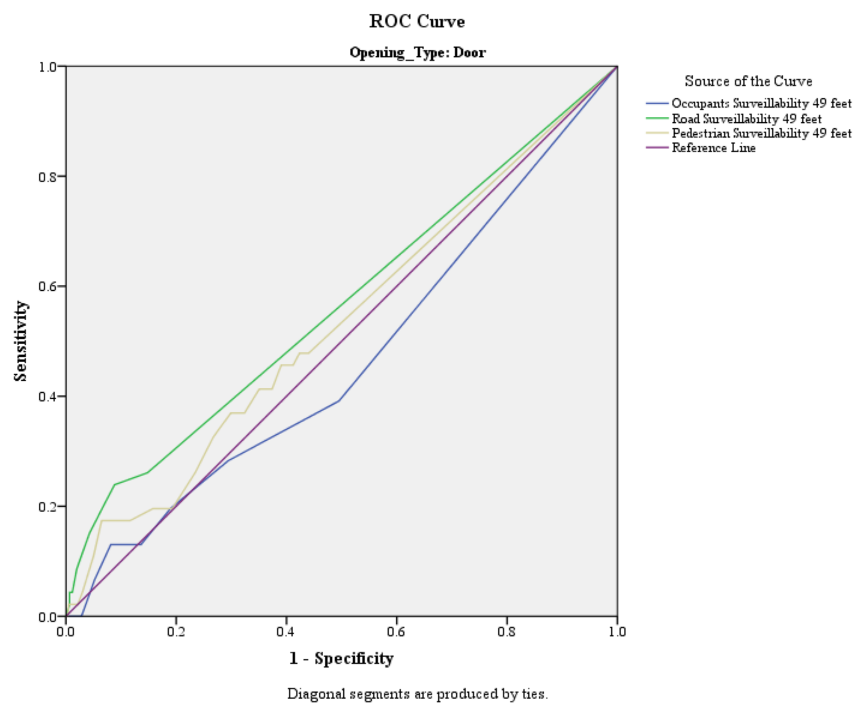


Figure 72. ROC curves for burglary commission through doors in relation to occupant, road and pedestrian surveillability within 49 feet of door openings (Source: Author).

Window openings. A logistic regression analysis was conducted to understand whether burglary commission through windows can be reliably predicted from knowledge of occupant surveillability (See Table 58). The test of the full model against a constant only model was statistically significant (χ^2 (1) = 6.93, p = 0.008). The Hosmer-Lemeshow test (χ^2 (6) = 5.41, p > 0.05) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value was of 0.03 indicated that the model is not accurate in predicting burglary commission through window openings.

According to the model, burglary commission through windows was associated with lower degrees of occupant surveillability (OR = 0.74; 95%CI = 0.56-0.96; p = 0.03). The odds ratio of 0.74 shows that burglary commission through windows is 0.74 times as likely (or about 26% less likely) with a one unit increase in occupant surveillability. In addition, the log of the odds of burglary commission through windows was negatively related to occupant surveillability. In fact, for every one unit increase in occupant surveillability, the log odds of burglary commission through windows decreases by 0.31. In other words, the more a window was surveyed by neighboring building openings, the less likely it was that that window would be chosen for burglary commission.

Model 2 includes eight additional theoretically important variables: building use, territoriality, diversity, maintenance, vacant lot, corner/middle lot, no-trespassing symbols and facing of building openings. The test of the full model against a constant only model was statistically significant (χ^2 (11) = 22.59, p = 0.02). According to the likelihood ratio test statistic, Model 2 is superior to Model 1 in terms of overall model fit. The H-L test (χ^2 (8) = 3.97, p > 0.05) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value of

0.11 indicated that the model was not very accurate in predicting burglary commission through windows openings. Hence, even though the contribution of independent variables in prediction of burglary commission through windows was statistically significant, the effect size was small.

According to the model, burglary commission through windows was associated with lower degrees of occupant surveillability (OR = 0.71; 95%CI = 0.52-0.97; $p < 0.05$). The odds ratio of 0.71 shows that burglary commission through windows is 0.71 times as likely (or about 29% less likely) with a one unit increase in occupant surveillability, holding all other independent variables constant. In addition, the log of the odds of burglary commission through windows was negatively related to occupant surveillability. In fact, for every one unit increase in occupant surveillability, the log odds of burglary commission through windows decreased by 0.34.

Next, logistic regression analyses were performed to understand whether burglary commission through windows can be reliably predicted from knowledge of road and pedestrian surveillability. The test of the full model against the constant only model for the road surveillability model (χ^2 (1) = 0.51, $p > 0.05$) and the pedestrian surveillability model (χ^2 (1) = 1.21, $p > 0.05$) were statistically insignificant (See Table 59 and Table 60).

Lastly, the area under the ROC curve for prediction of burglary commission through windows in relation to occupant surveillability gave a value of 0.33 (95%CI = 0.21-0.44; p = 0.01). The value of 0.33 confirmed that occupant surveillability is negatively associated with burglary commission through windows, but the model is not accurate in classifying true positive events. The area under the ROC curve for prediction of burglary commission through windows in relation to road and pedestrian surveillability gave values of 0.50 (95%CI = 0.37-0.64; $p > 0.05$) and 0.56 (95%CI = 0.43-0.70; $p > 0.05$) respectively. These values showed that the road and pedestrian surveillability models are neither significant nor accurate at classifying true positive events (See Table 60 and Figure 73).

Table 58

Logistic regression analysis of 2531 windows for burglary commissions in relation to occupant surveillability within 49 feet of window openings (Source: Author).

Independent and Control Variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	95% C.I. for Exp(B) Upper
Model 1								
Occupant surveillability 49 feet (Windows)	-0.31	0.14	4.97	1	0.026	0.74	0.56	0.96
Constant	-4.36	0.28	248.83	1	0.000	0.01		
Model 2								
Occupant surveillability 49 feet (Windows)	-0.34	0.16	4.70	1	0.030	0.71	0.52	0.97
Building Use (1 = 2 plus units)	0.01	0.51	0.00	1	0.983	1.01	0.37	2.74
Territoriality (1 = Completely fenced)	-1.24	0.55	5.04	1	0.025	0.29	0.10	0.85
Presence of facilities within 49 feet (1 = Yes)	-16.75	4904.82	0.00	1	0.997	0.00	0.00	
Adjacent vacant lot (1 = Yes)	0.41	0.80	0.26	1	0.610	1.50	0.31	7.16
Maintenance (1 = Maintained)	-0.21	0.47	0.20	1	0.657	0.81	0.32	2.05
Corner vs. middle lot (1 = Corner lot)	0.28	0.53	0.27	1	0.603	1.32	0.46	3.75
Presence of no-trespassing signs (1 = Yes)	0.72	0.56	1.69	1	0.194	2.06	0.69	6.12
Opening face (1 = Alley)	0.25	0.58	0.19	1	0.667	1.28	0.41	3.96
Opening face (1 = Regional)	-1.60	0.85	3.53	1	0.060	0.20	0.04	1.07
Opening face (1 = Neighborhood collector)	-0.30	1.10	0.07	1	0.786	0.74	0.09	6.41
Constant	-3.72	0.62	35.75	1	0.000	0.02		

Model Evaluation	Block1	df	Sig.	Block2	df	Sig.
Chi-square	6.93	1	0.008	22.59	11	0.020
-2 Log likelihood	216.82			201.16		
Cox and Snell (R square)	0.003			0.009		
Nagelkerke (R Square)	0.032			0.105		
Hosmer and Lemeshow Test (Chi-square)	5.41	6	0.492	3.97	8	0.860

Table 59

Logistic regression analysis of 2531 windows for burglary commissions in relation to road surveillability within 49 feet of window openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Road surveillability 49 feet (Windows)	0.11	0.14	0.59	1	0.443	1.11	0.85	1.45
Constant	-4.95	0.25	387.62	1	0.000	0.01		

Model Evaluation	Block1	df	Sig.
Chi-square	0.51	1	0.474
-2 Log likelihood	223.24		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.002		
Hosmer and Lemeshow Test (Chi-square)	0.68	1	0.409

Table 60

Logistic regression analysis of 2531 windows for burglary commissions in relation to pedestrian surveillability within 49 feet of window openings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Model 1								
Pedestrian surveillability 49 feet (Windows)	0.04	0.03	1.31	1	0.252	1.04	0.97	1.11
Constant	-5.06	0.30	294.06	1	0.000	0.01		

Model Evaluation	Block1	df	Sig.
Chi-square	1.21	1	0.272
-2 Log likelihood	222.54		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.006		
Hosmer and Lemeshow Test (Chi-square)	3.18	3	0.365

Table 61

ROC statistics for burglary commissions in relation to occupant, road and pedestrian surveillability models within 49 feet of window openings (Source: Author).

Independent Variables	Area	S.E.	Sig.	95% C.I. Lower	95% C.I. Upper
Occupant surveillability 49 feet (Windows)	0.33	0.06	0.010	0.21	0.44
Road surveillability 49 feet (Windows)	0.50	0.07	0.957	0.37	0.64
Pedestrian surveillability 49 feet (Windows)	0.56	0.07	0.331	0.43	0.70

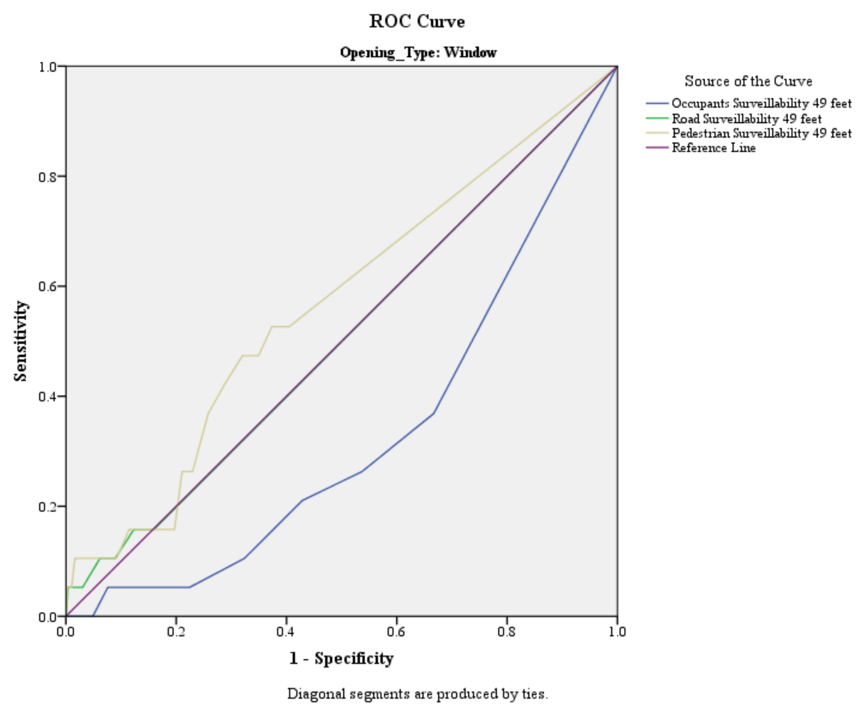


Figure 73. ROC curves for burglary commission through windows in relation to occupant, road and pedestrian surveillability within 49 feet of window openings (Source: Author).

5.3.2.3.2 Within 95 feet distance

All building openings. A logistic regression analysis was conducted to understand whether burglary commissions can be reliably predicted from knowledge of occupant surveillability (See Table 62). The test of the full model against the constant only model was statistically significant (χ^2 (1) = 7.23, p = 0.007). The Hosmer-Lemeshow test (χ^2 (6) = 4.47, p > 0.05) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value of 0.01 indicated that the model is not accurate in predicting burglary commissions.

According to the model, burglary commission was associated with lower degrees of occupant surveillability (OR = 0.89; 95%CI = 0.81-0.98; p < 0.05). The odds ratio of 0.89 shows that burglary commission is 0.89 times as likely (or about 11% less likely) with a one unit increase in occupant surveillability. In addition, the log of the odds of burglary commission was negatively related to occupant surveillability. In fact, for every one unit increase in occupant surveillability, the log odds of burglary commission decreased by 0.12. In other words, the more a building opening was surveyed by neighboring building openings, the less likely it was that that building opening would be chosen for burglary commission.

Model 2 includes eight additional theoretically important variables: building use, territoriality, diversity, maintenance, vacant lot, corner/middle lot, no-trespassing symbols and facing of building openings. The test of the full model against the constant only model was statistically significant (χ^2 (11) = 39.17, p < 0.001). According to the likelihood ratio test statistic, Model 2 was superior to Model 1 in terms of overall model fit. The H-L test (χ^2 (8) = 6.55, p > 0.05) suggested that the model was fit to the data well. However, the Nagelkerke R^2

value of 0.07 indicated that the model is not accurate in predicting burglary commissions. According to the model, after controlling for eight additional theoretically important variables, the significant contribution of the occupant surveillability variable to the model faded away (OR = 0.91; 95%CI = 0.83-1.01; p = 0.065).

Next, logistic regression analyses were performed to understand whether burglary commissions can be reliably predicted from knowledge of road and pedestrian surveillability. The test of the full model against the constant only model for the road surveillability model (χ^2 (1) = 0.67, $p > 0.05$) and the pedestrian surveillability model (χ^2 (1) = 0.62, $p > 0.05$) were statistically insignificant (See Table 63 and Table 64).

Lastly, the area under the ROC curve for prediction of burglary commission in relation to occupant surveillability gave a value of 0.40 (95%CI = 0.33-0.47; p = 0.005). The value of 0.40 confirmed that occupant surveillability is negatively associated with burglary commission, but the model is not very accurate in classifying true positive events. The area under the ROC curve for prediction of burglary commission in relation to road and pedestrian surveillability gave values of 0.52 (95%CI = 0.44-0.59; $p > 0.05$) and 0.51 (95%CI = 0.43-0.59; $p > 0.05$) respectively. These values showed that the road and pedestrian surveillability models are neither significant nor accurate at classifying true positive events (See Table 65 and Figure 74).

Table 62

Logistic regression analysis of 3179 building openings for burglary commissions in relation to occupant surveillability within 95 feet of building openings (Source: Author).

							95% C.I. for Exp(B)	
Independent and Control Variables	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Occupant surveillability 95 feet	-0.12	0.05	6.10	1	0.014	0.89	0.81	0.98
Constant	-3.53	0.17	437.17	1	0.000	0.03		
Model 2								
Occupant surveillability 95 feet	-0.09	0.05	3.41	1	0.065	0.91	0.83	1.01
Building Use (1 = 2 plus units)	0.42	0.27	2.50	1	0.114	1.53	0.90	2.58
Territoriality (1 = Completely fenced)	-1.04	0.30	11.99	1	0.001	0.35	0.20	0.64
Presence of facilities within 95 feet (1 = Yes)	-0.68	0.49	1.91	1	0.166	0.51	0.19	1.33
Adjacent vacant lot (1 = Yes)	0.86	0.43	4.01	1	0.045	2.37	1.02	5.54
Maintenance (1 = Maintained)	0.04	0.26	0.02	1	0.884	1.04	0.63	1.71
Corner vs. middle lot (1 = Corner lot)	0.38	0.29	1.73	1	0.189	1.46	0.83	2.58
Presence of no-trespassing signs (1 = Yes)	0.18	0.34	0.27	1	0.607	1.19	0.61	2.34
Opening face (1 = Alley)	0.58	0.35	2.75	1	0.097	1.79	0.90	3.55
Opening face (1 = Regional)	0.12	0.35	0.11	1	0.742	1.12	0.56	2.23
Opening face (1 = Neighborhood collector)	0.92	0.50	3.40	1	0.065	2.50	0.94	6.62
Constant	-3.76	0.37	106.24	1	0.000	0.02		

Model Evaluation	Model1	df	Sig.	Model2	df	Sig.
Chi-square	7.23	1	0.007	39.17	11	0.000
-2 Log likelihood	627.12			595.19		
Cox and Snell (R square)	0.002			0.012		
Nagelkerke (R Square)	0.013			0.068		
Hosmer and Lemeshow Test (Chi-square)	4.47	6	0.613	6.55	8	0.586

Table 63

Logistic regression analysis of 3179 building openings for burglary commissions in relation to road surveillability within 95 feet of building openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Road surveillability 95 feet	0.02	0.03	0.70	1	0.404	1.02	0.97	1.08
Constant	-3.98	0.18	471.65	1	0.000	0.02		

Model Evaluation	Model1	df	Sig.
Chi-square	0.67	1	0.411
-2 Log likelihood	633.68		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.001		
Hosmer and Lemeshow Test (Chi-square)	7.06	7	0.423

Table 64

Logistic regression analysis of 3179 building openings for burglary commissions in relation to pedestrian surveillability within 95 feet of building openings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	95% C.I. for Exp(B) Upper
Model 1								
Pedestrian surveillability 95 feet	0.00	0.01	0.63	1	0.427	1.00	0.99	1.02
Constant	-3.97	0.19	452.59	1	0.000	0.02		

Model Evaluation	Model1	df	Sig.
Chi-square	0.62	1	0.432
-2 Log likelihood	633.74		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.001		
Hosmer and Lemeshow Test (Chi-square)	6.21	7	0.515

Table 65

ROC statistics for burglary commissions in relation to occupant, road and pedestrian surveillability within 95 feet of building openings (Source: Author).

				95% C.I.	
Independent Variables	Area	S.E.	Sig.	Lower	Upper
Occupant surveillability 95 feet	0.40	0.04	0.005	0.33	0.47
Road surveillability 95 feet	0.52	0.04	0.632	0.44	0.59
Pedestrian surveillability 95 feet	0.51	0.04	0.774	0.43	0.59

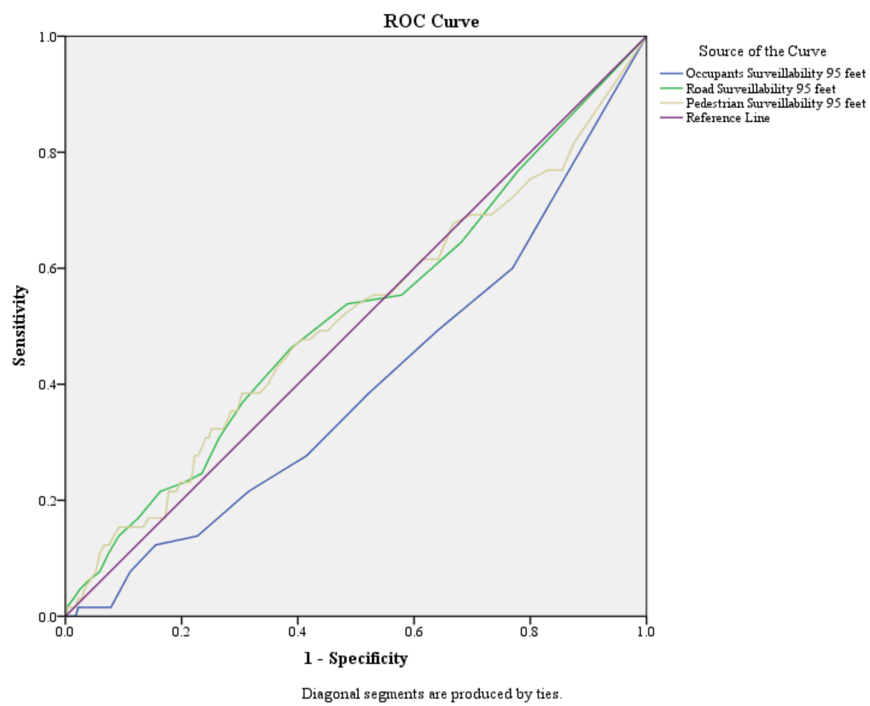


Figure 74. ROC curves for burglary commissions in relation to occupant, road and pedestrian surveillability within 95 feet of building openings (Source: Author).

Door openings. Logistic regression analyses were performed to understand whether burglary commission through doors can be reliably predicted from knowledge of occupant, road and pedestrian surveillability. The test of the full model against the constant only model for the occupant surveillability model (χ^2 (1) = 0.24, $p > 0.05$), the road surveillability model (χ^2 (1) = 1.97, $p > 0.05$) and the pedestrian surveillability model (χ^2 (1) = 0.98, $p > 0.05$) were statistically insignificant (See Table 66, Table 67 and Table 68).

Lastly, the area under the ROC curve for prediction of burglary commission through doors in relation to occupant, roads and pedestrian surveillability gave values of 0.51 (95%CI = 0.41-0.60; $p > 0.05$), 0.55 (95%CI = 0.46-0.64; $p > 0.05$) and 0.53 (95%CI = 0.43-0.62; $p > 0.05$) respectively. These values showed that the occupant, road and pedestrian surveillability measures are neither significant nor accurate at classifying true positive events (See Table 69 and Figure 75).

Table 66

Logistic regression analysis of 648 doors for burglary commissions in relation to occupant surveillability within 95 feet of door openings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Model 1								
Occupant surveillability 95 feet (Doors)	0.02	0.05	0.24	1	0.621	1.03	0.93	1.13
Constant	-2.63	0.20	178.21	1	0.000	0.07		

Model Evaluation	Model1	df	Sig.
Chi-square	0.24	1	0.627
-2 Log likelihood	331.78		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.001		
Hosmer and Lemeshow Test (Chi-square)	3.02	4	0.555

Table 67

Logistic regression analysis of 648 doors for burglary commissions in relation to road surveillability within 95 feet of door openings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Model 1								
Road surveillability 95 feet (Doors)	0.05	0.03	2.03	1	0.154	1.05	0.98	1.12
Constant	-2.80	0.23	144.16	1	0.000	0.06		

Model Evaluation	Model1	df	Sig.
Chi-square	1.97	1	0.160
-2 Log likelihood	330.04		
Cox and Snell (R square)	0.003		
Nagelkerke (R Square)	0.008		
Hosmer and Lemeshow Test (Chi-square)	6.06	6	0.416

Table 68

Logistic regression analysis of 648 doors for burglary commissions in relation to pedestrian surveillability within 95 feet of door openings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Model 1								
Pedestrian surveillability 95 feet (Doors)	0.01	0.01	1.00	1	0.318	1.01	0.99	1.02
Constant	-2.73	0.23	140.67	1	0.000	0.06		

Model Evaluation	Model1	df	Sig.
Chi-square	0.98	1	0.322
-2 Log likelihood	331.04		
Cox and Snell (R square)	0.002		
Nagelkerke (R Square)	0.004		
Hosmer and Lemeshow Test (Chi-square)	4.07	7	0.772

Table 69

ROC statistics for burglary commissions in relation to occupant, road and pedestrian surveillability within 95 feet distance of door openings (Source: Author).

Independent Variables	Area	S.E.	Sig.	95% C.I. Lower	95% C.I. Upper
Occupant surveillability 95 feet (Doors)	0.51	0.05	0.860	0.41	0.60
Road surveillability 95 feet (Doors)	0.55	0.05	0.246	0.46	0.64
Pedestrian surveillability 95 feet (Doors)	0.53	0.05	0.550	0.43	0.62

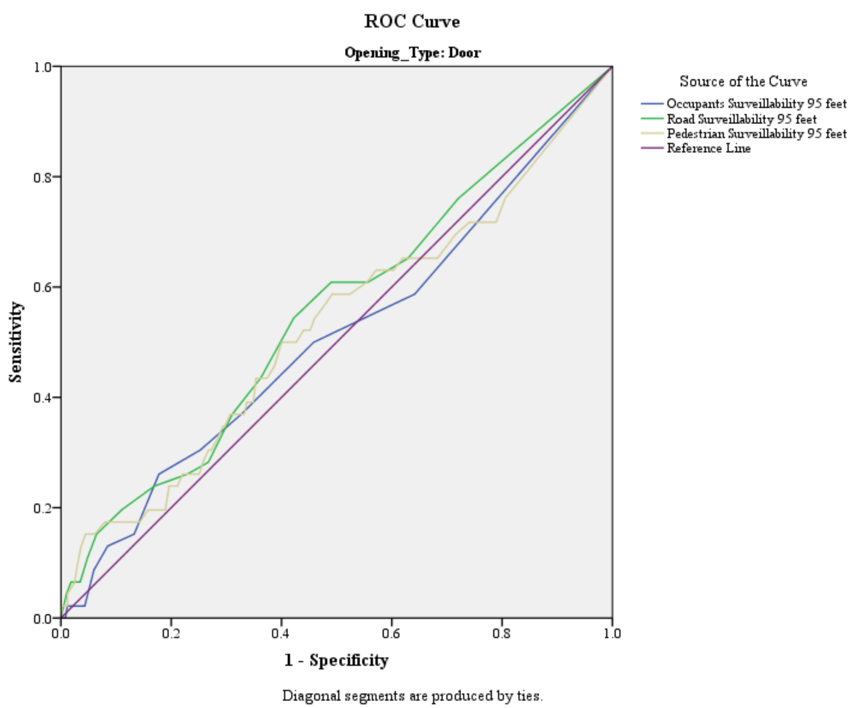


Figure 75. ROC curves for burglary commission through doors in relation to occupant, road and pedestrian surveillability within 95 feet of door openings (Source: Author).

Window openings. A logistic regression analysis was conducted to understand whether burglary commission through windows can be reliably predicted from knowledge of occupant surveillability (See Table 70). The test of the full model against a constant only model was statistically significant (χ^2 (1) = 5.24, p = 0.02). The Hosmer-Lemeshow test (χ^2 (7) = 7.82, p > 0.05) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value was of 0.02 indicated that the model was not accurate in predicting burglary commission through window openings.

According to the model, burglary commission through windows was associated with lower degrees of occupant surveillability (OR = 0.82; 95%CI = 0.68-0.99; p = 0.04). The odds ratio of 0.82 shows that burglary commission through windows is 0.82 times as likely (or about 18% less likely) with a one unit increase in occupant surveillability. In addition, the log of the odds of burglary commission through windows was negatively related to occupant surveillability. In fact, for every one unit increase in occupant surveillability, the log odds of burglary commission through windows decreases by 0.20. In other words, the more a window was surveyed by neighboring building openings, the less likely it was that that window would be chosen for burglary commission.

Model 2 includes eight additional theoretically important variables: building use, territoriality, diversity, maintenance, vacant lot, corner/middle lot, no-trespassing symbols and facing of building openings. The test of the full model against a constant only model was statistically significant (χ^2 (11) = 26.03, p = 0.006). According to the likelihood ratio test statistic, Model 2 is superior to Model 1 in terms of overall model fit. The H-L test (χ^2 (8) = 10.79, p > 0.05) suggested that the model was fit to the data well. However, the Nagelkerke R^2

value of 0.12 indicated that the model was not very accurate in predicting burglary commission through window openings.

According to the model, burglary commission through windows was associated with lower degrees of occupant surveillability (OR = 0.80; 95%CI = 0.65-1.00; $p = 0.04$). The odds ratio of 0.80 shows that burglary commission through windows is 0.80 times as likely (or about 20% less likely) with a one unit increase in occupant surveillability, holding all other independent variables constant. In addition, the log of the odds of burglary commission through windows was negatively related to occupant surveillability. In fact, for every one unit increase in occupant surveillability, the log odds of burglary commission through windows decreased by 0.22.

Next, logistic regression analyses were performed to understand whether burglary commission through windows can be reliably predicted from knowledge of road and pedestrian surveillability. The test of the full model against the constant only model for the road surveillability model (χ^2 (1) = 0.34, $p > 0.05$) and the pedestrian surveillability model (χ^2 (1) = 0.11, $p > 0.05$) were statistically insignificant (See Table 71 and Table 72).

Lastly, the area under the ROC curve for prediction of burglary commission through windows in relation to occupant surveillability gave a value of 0.36 (95%CI = 0.24-0.47; $p = 0.03$). The value of 0.36 confirmed that occupant surveillability is negatively associated with burglary commission through windows, but the model is not accurate in classifying true positive events. The area under the ROC curve for prediction of burglary commission through windows in relation to road and pedestrian surveillability gave values of 0.44 (95%CI = 0.32-0.57; $p >$

0.05) and 0.49 (95%CI = 0.37-0.61; $p > 0.05$) respectively. These values showed that the road and pedestrian surveillability models are neither significant nor accurate at classifying true positive events (See Table 73 and Figure 76).

Table 70

Logistic regression analysis of 2531 windows for burglary commissions in relation to occupant surveillability within 95 feet of window openings (Source: Author).

							95% C.I. for Exp(B)	
Independent and Control Variables	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Occupant surveillability 95 feet (Windows)	-0.20	0.10	4.06	1	0.044	0.82	0.68	0.99
Constant	-4.33	0.31	195.92	1	0.000	0.01		
Model 2								
Occupant surveillability 95 feet (Windows)	-0.22	0.11	3.93	1	0.048	0.80	0.65	1.00
Building Use (1 = 2 plus units)	0.21	0.51	0.17	1	0.684	1.23	0.45	3.36
Territoriality (1 = Completely fenced)	-1.34	0.55	5.81	1	0.016	0.26	0.09	0.78
Presence of facilities within 95 feet (1 = Yes)	-16.86	2338.76	0.00	1	0.994	0.00	0.00	
Adjacent vacant lot (1 = Yes)	0.88	0.79	1.23	1	0.268	2.40	0.51	11.30
Maintenance (1 = Maintained)	-0.13	0.47	0.08	1	0.779	0.88	0.35	2.21
Corner vs. middle lot (1 = Corner lot)	0.40	0.53	0.58	1	0.448	1.50	0.53	4.24
Presence of no-trespassing signs (1 = Yes)	0.56	0.57	0.99	1	0.321	1.76	0.58	5.33
Opening face (1 = Alley)	0.61	0.57	1.15	1	0.283	1.85	0.60	5.67
Opening face (1 = Regional)	-1.31	0.84	2.46	1	0.117	0.27	0.05	1.39
Opening face (1 = Neighborhood collector)	-0.13	1.10	0.01	1	0.904	0.87	0.10	7.61
Constant	-3.86	0.63	37.09	1	0.000	0.02		

Model Evaluation	Model1	df	Sig.	Model2	df	Sig.
Chi-square	5.24	1	0.022	26.03	11	0.006
-2 Log likelihood	218.51			197.73		
Cox and Snell (R square)	0.002			0.010		
Nagelkerke (R Square)	0.024			0.121		
Hosmer and Lemeshow Test (Chi-square)	7.82	7	0.349	10.79	8	0.214

Table 71

Logistic regression analysis of 2531 windows for burglary commissions in relation to road surveillability within 95 feet of window openings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	95% C.I. for Exp(B) Upper
Model 1								
Road surveillability 95 feet (Windows)	-0.03	0.06	0.32	1	0.570	0.97	0.87	1.08
Constant	-4.75	0.32	222.07	1	0.000	0.01		

Model Evaluation	Model1	df	Sig.
Chi-square	0.34	1	0.559
-2 Log likelihood	223.41		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.002		
Hosmer and Lemeshow Test (Chi-square)	3.24	7	0.862

Table 72

Logistic regression analysis of 2531 windows for burglary commissions in relation to pedestrian surveillability within 95 feet of window openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Pedestrian surveillability 95 feet (Windows)	0.00	0.01	0.11	1	0.742	1.00	0.97	1.02
Constant	-4.80	0.33	213.04	1	0.000	0.01		

Model Evaluation	Model1	df	Sig.
Chi-square	0.11	1	0.739
-2 Log likelihood	223.64		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.001		
Hosmer and Lemeshow Test (Chi-square)	5.61	8	0.690

Table 73

ROC statistics for burglary commissions in relation to occupant, road and pedestrian surveillability within 95 feet of window openings (Source: Author).

Independent Variables	Area	S.E.	Sig.	95% C.I.	
				Lower	Upper
Occupant surveillability 95 feet (Windows)	0.36	0.06	0.029	0.24	0.47
Road surveillability 95 feet (Windows)	0.44	0.06	0.389	0.32	0.57
Pedestrian surveillability 95 feet (Windows)	0.49	0.06	0.844	0.37	0.61

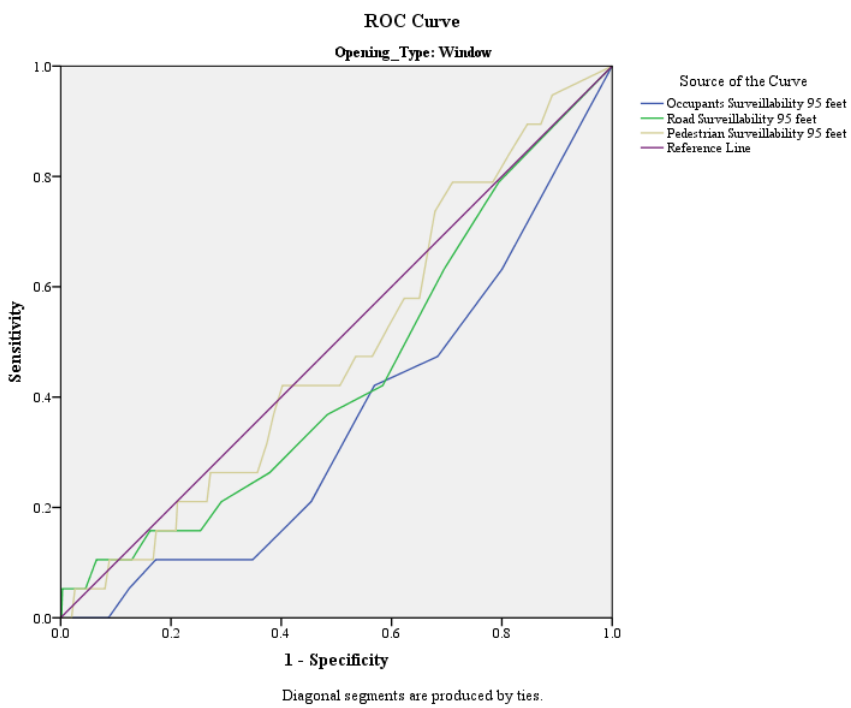


Figure 76. ROC curves for burglary commission through windows in relation to occupant, road and pedestrian surveillability within 95 feet of window openings (Source: Author).

5.3.2.3.3 Within 141 feet distance

All building openings. Logistic regression analyses were performed to understand whether burglary commission through doors can be reliably predicted from knowledge of occupant, road and pedestrian surveillability. The test of the full model against the constant only model for the occupant surveillability model (χ^2 (1) = 3.03, $p > 0.05$), the road surveillability model (χ^2 (1) = 0.65, $p > 0.05$) and the pedestrian surveillability model (χ^2 (1) = 0.29, $p > 0.05$) were statistically insignificant (See Table 74, Table 75 and Table 76).

The area under the ROC curve for prediction of burglary commission in relation to occupant surveillability gave a value of 0.42 (95%CI = 0.35-0.49; $p = 0.03$). Even though the regression model was statistically insignificant, the area under the ROC curve was statistically significant. The area under the ROC curve for prediction of burglary commission in relation to road and pedestrian surveillability gave values of 0.52 (95%CI = 0.44-0.59; $p > 0.05$) and 0.50 (95%CI = 0.43-0.58; $p > 0.05$) respectively. These values showed that the road and pedestrian surveillability models are neither significant nor accurate at classifying true positive events (See Table 77 and Figure 77).

Table 74

Logistic regression analysis of 3179 building openings for burglary commissions in relation to occupant surveillability within 141 feet of building openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Occupant surveillability 141 feet	-0.03	0.02	2.81	1	0.094	0.97	0.93	1.01
Constant	-3.59	0.20	337.73	1	0.000	0.03		

Model Evaluation	Model1	df	Sig.
Chi-square	3.03	1	0.082
-2 Log likelihood	631.32		
Cox and Snell (R square)	0.001		
Nagelkerke (R Square)	0.005		
Hosmer and Lemeshow Test (Chi-square)	7.23	7	0.405

Table 75

Logistic regression analysis of 3179 building openings for burglary commissions in relation to road surveillability within 141 feet of building openings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Model 1								
Road surveillability 141 feet	0.01	0.02	0.67	1	0.413	1.01	0.98	1.04
Constant	-3.97	0.18	471.46	1	0.000	0.02		

Model Evaluation	Model1	df	Sig.
Chi-square	0.65	1	0.420
-2 Log likelihood	633.70		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.001		
Hosmer and Lemeshow Test (Chi-square)	12.19	8	0.143

Table 76

Logistic regression analysis of 3179 building openings for burglary commissions in relation to pedestrian surveillability within 141 feet of building openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Pedestrian surveillability 141 feet	0.00	0.00	0.30	1	0.585	1.00	1.00	1.01
Constant	-3.94	0.19	441.84	1	0.000	0.02		

Model Evaluation	Model1	df	Sig.
Chi-square	0.29	1	0.588
-2 Log likelihood	634.06		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.001		
Hosmer and Lemeshow Test (Chi-square)	7.38	8	0.496

Table 77

ROC statistics for burglary commissions in relation to occupant, road and pedestrian surveillability within 141 feet of building openings (Source: Author).

				95% C.I.	
Independent Variables	Area	S.E.	Sig.	Lower	Upper
Occupant surveillability 141 feet	0.42	0.04	0.027	0.35	0.49
Road surveillability 141 feet	0.52	0.04	0.642	0.44	0.59
Pedestrian surveillability 141 feet	0.50	0.04	0.895	0.43	0.58

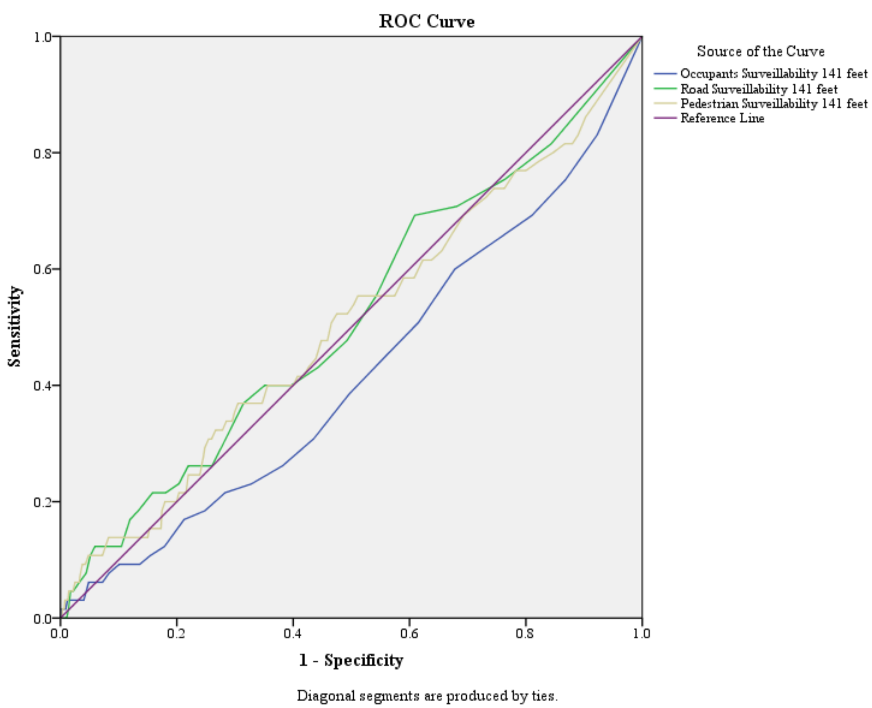


Figure 77. ROC curves for burglary commissions in relation to occupant, road and pedestrian surveillability within 141 feet of building openings (Source: Author).

Door openings. Logistic regression analyses were performed to understand whether burglary commission through doors can be reliably predicted from knowledge of occupant, road and pedestrian surveillability. The test of the full model against the constant only model for the occupant surveillability model (χ^2 (1) = 0.41, $p > 0.05$), the road surveillability model (χ^2 (1) = 1.86, $p > 0.05$) and the pedestrian surveillability model (χ^2 (1) = 1.00, $p > 0.05$) were statistically insignificant (See Table 78, Table 79 and Table 80).

The area under the ROC curve for prediction of burglary commission through doors in relation to occupant, roads and pedestrian surveillability gave values of 0.45 (95%CI = 0.36-0.54; $p > 0.05$), 0.55 (95%CI = 0.46-0.64; $p > 0.05$) and 0.53 (95%CI = 0.44-0.62; $p > 0.05$) respectively. These values showed that the occupant, road and pedestrian surveillability measures are neither significant nor accurate at classifying true positive events (See Table 81 and Figure 78).

Table 78

Logistic regression analysis of 648 doors for burglary commissions in relation to occupant surveillability within 141 feet of door openings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Model 1								
Occupant surveillability 141 feet (Doors)	-0.01	0.02	0.40	1	0.526	0.99	0.94	1.03
Constant	-2.46	0.23	118.96	1	0.000	0.09		

Model Evaluation	Model1	df	Sig.
Chi-square	0.41	1	0.520
-2 Log likelihood	331.60		
Cox and Snell (R square)	0.001		
Nagelkerke (R Square)	0.002		
Hosmer and Lemeshow Test (Chi-square)	7.08	8	0.528

Table 79

Logistic regression analysis of 648 doors for burglary commissions in relation to road surveillability within 141 feet of door openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Road surveillability 141 feet (Doors)	0.03	0.02	1.93	1	0.164	1.03	0.99	1.07
Constant	-2.79	0.23	146.48	1	0.000	0.06		

Model Evaluation	Model1	df	Sig.
Chi-square	1.86	1	0.172
-2 Log likelihood	330.15		
Cox and Snell (R square)	0.003		
Nagelkerke (R Square)	0.007		
Hosmer and Lemeshow Test (Chi-square)	6.79	7	0.451

Table 80

Logistic regression analysis of 648 doors for burglary commissions in relation to pedestrian surveillability within 141 feet of door openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Pedestrian surveillability 141 feet (Doors)	0.00	0.00	1.03	1	0.311	1.00	1.00	1.01
Constant	-2.73	0.23	142.05	1	0.000	0.06		

Model Evaluation	Model1	df	Sig.
Chi-square	1.00	1	0.317
-2 Log likelihood	331.01		
Cox and Snell (R square)	0.002		
Nagelkerke (R Square)	0.004		
Hosmer and Lemeshow Test (Chi-square)	7.42	7	0.386

Table 81

ROC statistics for burglary commissions in relation to occupant, road and pedestrian surveillability within 141 feet of door openings (Source: Author).

Independent Variables	Area	S.E.	Sig.	95% C.I. Lower	95% C.I. Upper
Occupant surveillability 141 feet (Doors)	0.45	0.04	0.275	0.36	0.54
Road surveillability 141 feet (Doors)	0.55	0.05	0.305	0.46	0.64
Pedestrian surveillability 141 feet (Doors)	0.53	0.05	0.522	0.44	0.62

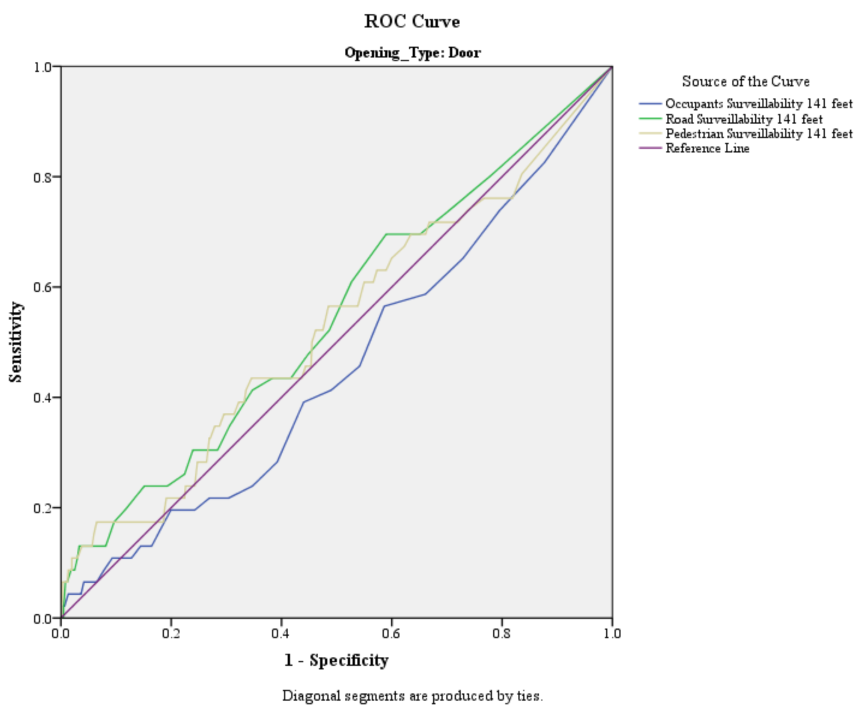


Figure 78. ROC curves for burglary commission through doors in relation to occupant, road and pedestrian surveillability within 141 feet of door openings (Source: Author).

Windows openings. Logistic regression analyses were performed to understand whether burglary commission through doors can be reliably predicted from knowledge of occupant, road and pedestrian surveillability. The test of the full model against the constant only model for the occupant surveillability model (χ^2 (1) = 1.01, $p > 0.05$), the road surveillability model (χ^2 (1) = 0.17, $p > 0.05$) and the pedestrian surveillability model (χ^2 (1) = 0.22, $p > 0.05$) were statistically insignificant (See Table 82, Table 83 and Table 84).

The area under the ROC curve for prediction of burglary commission through doors in relation to occupant, roads and pedestrian surveillability gave values of 0.44 (95%CI = 0.32-0.57; $p > 0.05$), 0.48 (95%CI = 0.35-0.60; $p > 0.05$) and 0.49 (95%CI = 0.37-0.60; $p > 0.05$) respectively. These values showed that the occupant, road and pedestrian surveillability measures are neither significant nor accurate at classifying true positive events (See Table 85 and Figure 79).

Table 82

Logistic regression analysis of 2531 windows for burglary commissions in relation to occupant surveillability within 141 feet of window openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Occupant surveillability 141 feet (Windows)	-0.04	0.04	0.93	1	0.334	0.96	0.89	1.04
Constant	-4.58	0.37	156.09	1	0.000	0.01		

Model Evaluation	Model1	df	Sig.
Chi-square	1.01	1	0.314
-2 Log likelihood	222.74		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.005		
Hosmer and Lemeshow Test (Chi-square)	3.11	7	0.874

Table 83

Logistic regression analysis of 2531 windows for burglary commissions in relation to road surveillability within 141 feet of window openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Road surveillability 141 feet (Windows)	-0.01	0.03	0.16	1	0.686	0.99	0.93	1.05
Constant	-4.79	0.32	220.77	1	0.000	0.01		

Model Evaluation	Model1	df	Sig.
Chi-square	0.17	1	0.680
-2 Log likelihood	223.58		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.001		
Hosmer and Lemeshow Test (Chi-square)	7.45	8	0.489

Table 84

Logistic regression analysis of 2531 windows for burglary commissions in relation to pedestrian surveillability within 141 feet of window openings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Pedestrian surveillability 141 feet (Windows)	0.00	0.01	0.21	1	0.648	1.00	0.98	1.01
Constant	-4.77	0.33	204.85	1	0.000	0.01		

Model Evaluation	Model1	df	Sig.
Chi-square	0.22	1	0.642
-2 Log likelihood	223.53		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.001		
Hosmer and Lemeshow Test (Chi-square)	8.17	8	0.417

Table 85

ROC statistics for burglary commissions in relation to occupant, road and pedestrian surveillability within 141 feet of window openings (Source: Author).

				95% C.I.	
Independent Variables	Area	S.E.	Sig.	Lower	Upper
Occupant surveillability 141 feet (Windows)	0.44	0.06	0.398	0.32	0.57
Road surveillability 141 feet (Windows)	0.48	0.06	0.708	0.35	0.60
Pedestrian surveillability 141 feet (Windows)	0.49	0.06	0.843	0.37	0.60

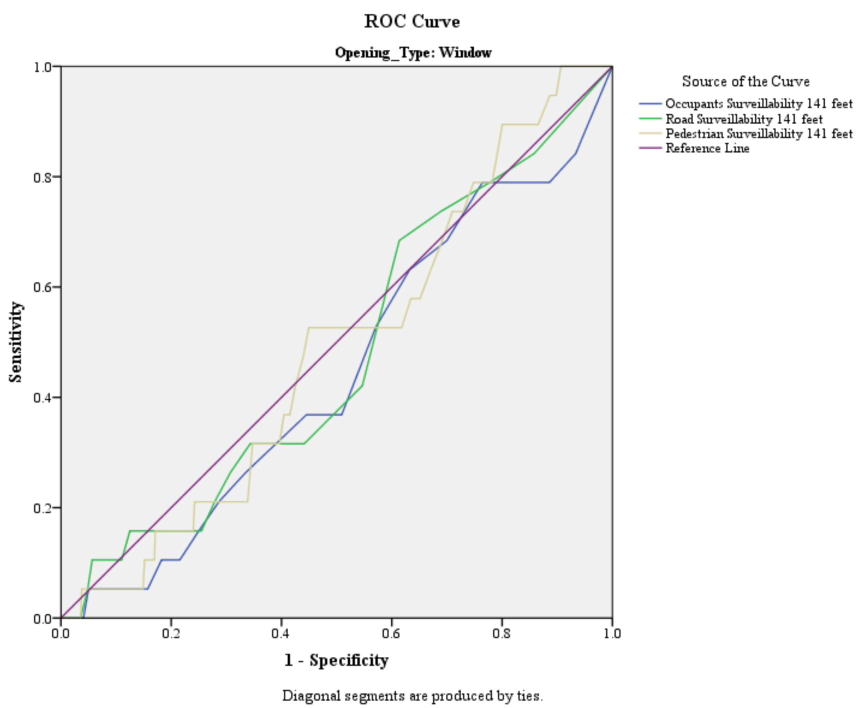


Figure 79. ROC curves for burglary commission through windows in relation to occupant, road and pedestrian surveillability within 141 feet of window openings (Source: Author).

5.3.2.3.4 Binary logistic regression in summary

I conducted binary logistic regressions to make predictions regarding the most likely entry points of burglaries from the knowledge of occupant, road and pedestrian surveillability (See Table 86). The following hypothesis was proposed in the introductory chapter of this dissertation:

- A burglar's point of entry can be reliably predicted from the knowledge of occupant, road and pedestrian surveillability.

The log of the odds of burglary commission was negatively related to occupant surveillability within 49 and 95 feet of building openings, and positively related to road surveillability within 49 feet of building openings in univariate analysis. The log of the odds of burglary commission in multivariate analysis was only significant for occupant surveillability within 49 feet of building openings.

The log of the odds of burglary commission through doors was positively related to road surveillability within 49 feet of building openings in univariate analysis. And the log of the odds of burglary commission through windows was negatively related to occupant surveillability within 49 and 95 feet of building openings in univariate and multivariate analyses.

In short, the Nagelkerke R^2 value of significant logistic regressions analyses ranged between 0.01 and 0.11 indicating that a burglary point of entry cannot be reliably predicted from knowledge of occupant and road surveillability. Nevertheless, occupant and road surveillability had a small effect in burglary commissions.

Table 86

Logistic regression analysis of building openings, door openings and window openings for burglary commission in relation to pedestrian, road and occupant surveillability (Source: Author).

	49 feet				95 feet				141 feet			
Independent Variables	M1	Sig.	M2	Sig.	M1	Sig.	M2	Sig.	M1	Sig.	M2	Sig.
Occupant surveillability	0.79	0.001	0.83	0.027	0.89	0.014	0.91	0.065	0.97	0.094	---	---
Road surveillability	1.17	0.033	---	---	1.02	0.404	---	---	1.01	0.413	---	---
Pedestrian surveillability	1.03	0.094	---	---	1.00	0.427	---	---	1.00	0.585	---	---
Occupant surveillability (Door)	0.97	0.690	---	---	1.03	0.621	---	---	0.99	0.526	---	---
Road surveillability (Door)	1.35	0.002	1.27	0.039	1.05	0.154	---	---	1.03	0.164	---	---
Pedestrian surveillability (Door)	1.03	0.307	---	---	1.01	0.318	---	---	1.00	0.311	---	---
Occupant surveillability (Window)	0.74	0.026	0.71	0.030	0.82	0.044	0.80	0.048	0.96	0.334	---	---
Road surveillability (Window)	1.11	0.443	---	---	0.97	0.570	---	---	0.99	0.686	---	---
Pedestrian surveillability (Window)	1.04	0.252	---	---	1.00	0.742	---	---	1.00	0.648	---	---

Note: M1 stands for Exp(B) for model 1, and M2 stands for Exp(B) model 2.

5.4 Statistical Analysis at the Building level

The following sections discuss the relationship between the degree of natural surveillance and residential burglaries at the building level. I analyzed vulnerability of buildings to burglary victimization at three distance measures of 49, 95 and 141 feet. The results of descriptive sand inferential statistics are discussed below.

5.4.1 Descriptive statistics

The following section offers a breadth of information on descriptive statistics. The explore procedure was first conducted to identify missing values and outliers and to evaluate normality of independent variables. No missing values were observed. However, visual inspection of the histogram and assessment of skeweness and kurtosis values indicate the distribution of the distribution of occupant, road and pedestrian surveillability at three distance measures of 49, 95 and 141 feet is positively skewed, with most of the scores on the lowest range. In addition, the results of the Kolmogorov-Smirnov tests showed that none of the distributions are normal. Thus, I used non-parametric tests and techniques robust to violations of normality for statistical analysis. Statistics are categorized according to distance measures of surveillability and tabulated in Table 87.

5.4.1.1 Within 49 feet distance

Occupant surveillability of buildings ranged from 0 to 122, with a mean of 29.66 (n = 224, SD = 17.65). Burglarized buildings had lower mean of occupant surveillability (n = 62, M = 26.34, SD = 19.14) than non-burglarized buildings (n = 162, M = 30.93, SD = 16.93). In addition, the number of visible sightlines to burglarized buildings ranged from 0 and 89, while that number ranged from 3 and 122 for non-burglarized buildings.

Road surveillability of buildings ranged from 0 to 61, with a mean of 6.46 (n = 224, SD = 11.33). Burglarized buildings had higher mean of road surveillability (n = 62, M = 10.16, SD = 14.77) than non-burglarized buildings (n = 162, M =5.05, SD = 9.37). Range of visible sightlines for burglarized and non-burglarized buildings was almost identical.

Pedestrian surveillability of buildings ranged from 0 to 234, with a mean of 55.48 (n = 224, SD = 43.97). Burglarized buildings had higher mean of pedestrian surveillability (n = 62, M = 65.63, SD = 51.29) than non-burglarized buildings (n = 162, M = 51.60, SD = 40.43). In addition, the number of visible sightlines to burglarized buildings ranged from 0 and 196, while that number ranged from 0 and 234 for non-burglarized buildings.

In summary, burglarized buildings had lower degrees occupant surveillability compared to non-burglarized ones. In addition, higher degrees road and pedestrian surveillability were observed for burglarized building openings compared to non-burglarized ones.

5.4.1.2 Within 95 feet distance

Occupant surveillability of buildings ranged from 3 to 169, with a mean of 45.00 (n = 224, SD = 28.16). Burglarized buildings had higher mean of occupant surveillability (n = 62, M = 45.63, SD = 36.81) than non-burglarized buildings (n = 162, M = 44.76, SD = 24.18). In addition, the number of visible sightlines to burglarized buildings ranged from 3 and 169, while that number ranged from 0 and 130 for non-burglarized buildings.

Road surveillability of buildings ranged from 0 to 179, with a mean of 61.25 (n = 224, SD = 35.22). Burglarized buildings had higher mean of road surveillability (n = 62, M = 66.76, SD = 40.86) than non-burglarized buildings (n = 162, M = 59.14, SD = 32.70). Range of visible sightlines for burglarized and non-burglarized buildings was almost identical.

Pedestrian surveillability of buildings ranged from 2 to 864, with a mean of 287.54 (n = 224, SD = 144.94). Burglarized buildings had higher mean of pedestrian surveillability (n = 62, M = 301.50, SD = 165.05) than non-burglarized buildings (n = 224, M = 282.20, SD = 136.64). In addition, the number of visible sightlines to burglarized buildings ranged from 5 and 701, while that number ranged from 2 and 864 for non-burglarized buildings.

In summary, burglarized buildings had higher degrees occupant, road and pedestrian surveillability compared to non-burglarized ones.

5.4.1.3 Within 141 feet distance

Occupant surveillability of buildings ranged from 8 to 296, with a mean of 115.33 (n = 224, SD = 56.22). Burglarized buildings had lower mean of occupant surveillability (n = 62, M = 104.40, SD = 57.83) than non-burglarized buildings (n = 162, M = 119.52, SD = 55.21). Range of visible sightlines for burglarized and non-burglarized buildings was almost identical.

Road surveillability of buildings ranged from 0 to 328, with a mean of 104.90 (n = 224, SD = 61.50). Burglarized buildings had higher mean of road surveillability (n = 62, M = 112.23, SD = 70.74) than non-burglarized buildings (n = 162, M = 102.10, SD = 57.57). In addition, the number of visible sightlines to burglarized buildings ranged from 4 and 298, while that number ranged from 0 and 328 for non-burglarized buildings.

Pedestrian surveillability of buildings ranged from 3 to 1592, with a mean of 505.30 (n = 224, SD = 266.44). Burglarized buildings had higher mean of pedestrian surveillability (n = 62, M = 520.74, SD = 298.79) than non-burglarized buildings (n = 162, M = 499.40, SD = 253.73). In addition, the number of visible sightlines to burglarized buildings ranged from 5 and 1294, while that number ranged from 3 and 1592 for non-burglarized buildings.

In summary, burglarized buildings had lower degrees of occupant surveillability compared to non-burglarized ones. In addition, higher degrees road and pedestrian surveillability were observed for burglarized building openings compared to non-burglarized ones.

Table 87

Descriptive statistics for occupant, road and pedestrian surveillability within 49, 95 and 141 feet of buildings (Source: Author).

	49 feet					
Independent Variables	N	Mean	Mode	SD	Min	Max
Occupant surveillability (49 feet)	224	29.66	25	17.65	0	122
Road surveillability	224	6.46	0	11.33	0	61
Pedestrian surveillability	224	55.48	38	43.97	0	234
Occupant surveillability (95 feet)	224	45.00	33	28.16	3	169
Road surveillability	224	61.25	36a	35.22	0	179
Pedestrian surveillability	224	287.54	207	144.94	2	864
Occupant surveillability (141 feet)	224	115.33	92	56.22	8	296
Road surveillability	224	104.90	75	61.50	0	328
Pedestrian surveillability	224	505.30	376a	266.44	3	1592

	Burglarized						Not Burglarized					
Independent Variables	N	Mean	Mode	SD	Min	Max	N	Mean	Mode	SD	Min	Max
Occupant surveillability (49 feet)	62	26.34	11	19.14	0	89	162	30.93	23	16.93	3	122
Road surveillability	62	10.16	0	14.77	0	57	162	5.05	0	9.37	0	61
Pedestrian surveillability	62	65.63	2b	51.29	0	196	162	51.60	0b	40.34	0	234
Occupant surveillability (95 feet)	62	45.63	13b	36.81	3	169	162	44.76	33	24.18	5	130
Road surveillability	62	66.76	44b	40.86	1	179	162	59.14	39	32.70	0	177
Pedestrian surveillability	62	301.50	232b	165.05	5	701	162	282.20	207	136.64	2	864
Occupant surveillability (141 feet)	62	104.40	92	57.83	10	296	162	119.52	143	55.21	8	292
Road surveillability	62	112.23	4b	70.74	4	298	162	102.10	75	57.57	0	328
Pedestrian surveillability	62	520.74	397b	298.79	5	1294	162	499.40	376b	253.73	3	1592

5.4.2 Inferential statistics

Inferential statistics used in this study are Spearman's rank correlation, Mann-Whitney U test and binary logistic regression. Non-parametric tests and techniques robust to violations of normality are used because; (a) the distributions of occupant, road and pedestrian surveillability are positively skewed, with most of the scores on the lowest range, also (b) the results of the Kolmogorov-Smirnov tests showed that the distributions of our independent variables are not normal.

5.4.2.1 Spearman's rank correlation

Spearman's rank correlation was performed to determine the relationship between the degree of occupant, road and pedestrian surveillability and residential burglaries. Statistics are presented according to distance measures and tabulated in Table 88.

49 feet distance. The results of Spearman's correlation analysis revealed a significant weak negative correlation between occupant surveillability and residential burglaries ($r = -0.14$, $p < 0.05$). In addition, a significant weak direct correlation was observed between road surveillability and residential burglaries ($r = 0.18$, $p = 0.006$). No significant relationship was observed between pedestrian surveillability and residential burglaries ($r = 0.10$, $p > 0.05$). However, the relationship between pedestrian surveillability and residential burglary is direct.

95 feet distance. The results of Spearman's correlation analysis revealed no significant relationship between occupant ($r = -0.08$, $p > 0.05$), road ($r = 0.07$, $p > 0.05$) and pedestrian ($r = 0.05$, $p > 0.05$) surveillability and residential burglaries. However, the relationship between occupant surveillability and residential burglaries is inverse and the relationships between road and pedestrian surveillability and burglary commissions are direct.

141 feet distance. The results of Spearman's correlation analysis revealed no significant relationship between occupant (r = -0.13, $p > 0.05$), road (r = 0.04, $p > 0.05$) and pedestrian (r = 0.02, $p > 0.05$) surveillability and residential burglaries. However, the relationship between occupant surveillability and residential burglaries is inverse and the relationships between road and pedestrian surveillability and burglary commissions are direct.

5.4.2.1.1 Spearman's rank correlation in summary

I conducted Spearman's rank correlation to determine the relationship between the degree of occupant, road and pedestrian surveillability and residential burglaries (See Table 88). The following hypothesis was proposed in the introductory chapter of this dissertation:

- There is a statistically significant inverse relationship between the degree of occupant, road and pedestrian surveillability and residential burglary victimization.

The results revealed that occupant surveillability within 49 feet of buildings correlated significantly inverse with residential burglary. As one distance from buildings (i.e. from 49 feet to 95 feet and to 141 feet), the relationship between occupant surveillability and residential burglary stays inverse but loses its statistical significance. Road surveillability was found to be positively related to residential burglary at 49 feet of buildings. This relation lost its significate within 95 and 141 feet of buildings. Lastly, the relationship between pedestrian surveillability and residential burglary is direct but insignificant at all distances measures of surveillability.

Table 88

Spearman's rank correlation for the relationship between residential burglaries and occupant, road and pedestrian surveillability within 49, 95 and 141 feet of buildings (Source: Author).

	49 feet		95 feet		141 feet	
Independent Variables	Coefficients	Sig.	Coefficients	Sig.	Coefficients	Sig.
Occupant surveillability	-0.14	0.041	-0.08	0.221	-0.13	0.059
Road surveillability	0.18	0.006	0.07	0.300	0.04	0.574
Pedestrian surveillability	0.10	0.123	0.05	0.483	0.02	0.712

Burglarized buildings are codes as 1, and non-burglarized building openings as 0. Coefficients show the relationship between visibility measures and the dichotomous variable of burglary commission.

5.4.2.2 Mann-Whitney U test

Mann-Whitney U test was performed to determine whether the degree of occupant, road and pedestrian surveillability differ between burglarized and non-burglarized buildings. Statistics are presented according to distance measures and tabulated in Table 89.

49 feet distance. The results of Mann-Whitney U test showed that burglarized buildings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized buildings ($U = 4136.00$, $Z = -2.04$, $p < 0.05$). In addition, burglarized buildings had statistically significant higher mean rank of road surveillability compared to non-burglarized buildings ($U = 3888.00$, $Z = -2.75$, $p = 0.006$). No statistically significant difference was observed between the mean rank of pedestrian surveillability for burglarized and non-burglarized buildings ($U = 4352.50$, $Z = -1.54$, $p > 0.05$). However, burglarized buildings had higher mean rank of occupant surveillability compared to non-burglarized buildings.

95 feet distance. The results of Mann-Whitney U test showed no statistically significant difference between the mean rank of occupant ($U = 4490.00$, $Z = -1.23$, $p > 0.05$), road ($U = 4571.00$, $Z = -1.04$, $p > 0.05$) and pedestrian ($U = 4717.00$, $Z = -0.70$, $p > 0.05$) surveillability for burglarized and non-burglarized buildings. However, burglarized buildings had lower mean rank of occupant surveillability and higher mean rank of road and pedestrian surveillability compared to non-burglarized buildings.

141 feet distance. The results of Mann-Whitney U test showed no statistically significant difference between the mean rank of occupant ($U = 4204.00$, $Z = -1.89$, $p > 0.05$), road ($U = 4777.50$, $Z = -0.56$, $p > 0.05$) and pedestrian ($U = 4861.50$, $Z = -0.37$, $p > 0.05$) surveillability for burglarized and non-burglarized buildings. However, burglarized buildings had lower mean rank of occupant surveillability and higher mean rank of road and pedestrian surveillability compared to non-burglarized buildings.

5.4.2.2.1 Mann-Whitney U test in summary

I conducted Mann-Whitney U test to determine whether the degree of occupant, road and pedestrian surveillability differ between burglarized and non-burglarized buildings (See Table 89). The following hypothesis was proposed in the introductory chapter of this dissertation:

- Burglarized buildings have statistically significant lower mean of occupant, road and pedestrian surveillability compared to non-burglarized buildings.

The results revealed that burglarized buildings had lower mean rank of occupant surveillability and higher mean rank of road surveillability compared to non-burglarized buildings at all 3 distance measures of surveillability. Mean differences were statistically significant at 49 feet of buildings. In addition, burglarized buildings had higher mean rank of pedestrian surveillability compared to non-burglarized buildings. However, the mean rank of pedestrian surveillability did not reach statistical significant at any distance measure of surveillability.

Table 89

Mann-Whitney U test for mean differences between occupant, road and pedestrian surveillability for burglarized and non-burglarized buildings (Source: Author).

Independent Variables	Z	Sig.	Mann-Whitney U	Not Burglarized Mean Rank	Burglarized Mean Rank
Occupant surveillability (49 feet)	-2.04	0.041	4136.00	117.97	98.21
Road surveillability	-2.75	0.006	3888.00	105.50	130.79
Pedestrian surveillability	-1.54	0.123	4352.50	108.37	123.30
Occupant surveillability (95 feet)	-1.23	0.220	4490.00	115.78	103.92
Road surveillability	-1.04	0.299	4571.00	109.72	119.77
Pedestrian surveillability	-0.70	0.482	4717.00	110.62	117.42
Occupant surveillability (141 feet)	-1.89	0.059	4204.00	117.55	99.31
Road surveillability	-0.56	0.573	4777.50	110.99	116.44
Pedestrian surveillability	-0.37	0.711	4861.50	111.51	115.09

	49 feet		95 feet		141 feet	
Independent Variables	Mann-Whitney	Sig.	Mann-Whitney	Sig.	Mann-Whitney	Sig.
Occupant surveillability	4136.00	0.041	4490.00	0.220	4204.00	0.059
Road surveillability	3888.00	0.006	4571.00	0.299	4777.50	0.573
Pedestrian surveillability	4352.50	0.123	4717.00	0.482	4861.50	0.711

5.4.2.3 Binary Logistic Regression

Logistic regression analysis was conducted to make predictions regarding the most likely residential burglaries from knowledge of occupant, road and pedestrian surveillability. In addition, performance of the binary logistic models was assessed through receiver operating characteristic (ROC) curves. The area under of the ROC curve shows accuracy or performance of logistic regression. Models are less accurate when curves are closer to the 45-degree baseline. In addition, models are not accurate when curves intersect the 45-degree diagonal line.

5.4.2.3.1 49 feet distance

First, a logistic regression analysis was conducted to understand whether residential burglaries can be reliably predicted from knowledge of occupant surveillability (See Table 90). The test of the full model against the constant only model was statistically insignificant (χ^2 (1) = 3.23, $p > 0.05$).

Next, a logistic regression analysis was performed to understand whether residential burglaries can be reliably predicted from knowledge of road surveillability (See Table 91). The test of the full model against the constant only model was statistically significant (χ^2 (1) = 8.36, p = 0.004). The Hosmer-Lemeshow test (χ^2 (5) = 4.22, $p > 0.05$) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value of 0.05 indicated that the model was not accurate in predicting residential burglaries.

According to the model, residential burglary is associated with higher degrees of road surveillability (OR = 1.04; 95%CI = 1.01-1.06; p = 0.004). The odds ratio of 1.04 shows that residential burglary is 1.04 times as likely (or about 4% more likely) with a one unit increase in road surveillability. In addition, the log of the odds of residential burglary was positively related to road surveillability. In fact, for every one unit increase in road surveillability, the log odds of residential burglary increased by 0.04. In other words, the more a building was surveyed from road, the less likely it was that that building would be chosen for burglary.

Model 2 includes seven additional theoretically important variables: building use, diversity, maintenance, vacant lot, corner/middle lot, no-trespassing symbols and facing of buildings. The test of the full model against the constant only model was statistically significant (χ^2 (8) = 20.33, p = 0.009). According to the likelihood ratio test statistic, Model 2 was superior to Model 1 in terms of overall model fit. The H-L test (χ^2 (7) = 11.34, p > 0.05) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value of 0.13 indicated that the model was not very accurate in predicting residential burglary.

According to the model, after controlling for seven additional theoretically important variables, residential burglary was associated with higher degrees of road surveillability (OR = 1.04; 95%CI = 1.00-1.08; p < 0.05). The odds ratio of 1.04 shows that residential burglary is 1.04 times as likely (or about 4% more likely) with a one unit increase in road surveillability. In addition, the log of the odds of residential burglary was positively related to road surveillability. In fact, for every one unit increase in road surveillability, the log odds of residential burglary increased by 0.04. In other words, the more a building was surveyed from road, the less likely it was that that building would be chosen for burglary.

Then, a logistic regression analysis was performed to understand whether residential burglary can be reliably predicted from knowledge of pedestrian surveillability (See Table 92). The test of the full model against the constant only model was statistically significant (χ^2 (1) = 4.37, $p < 0.05$). The Hosmer-Lemeshow test (χ^2 (8) = 10.09, $p > 0.05$) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value of 0.03 indicated that the model was not accurate in predicting residential burglary.

According to the model, residential burglary is associated with higher degrees of pedestrian surveillability (OR = 1.01; 95%CI = 1.00-1.01; $p < 0.05$). The odds ratio of 1.01 shows that residential burglary is 1.01 times as likely (or about 1% more likely) with a one unit increase in pedestrian surveillability. In addition, the log of the odds of residential burglary was positively related to pedestrian surveillability. In fact, for every one unit increase in road surveillability, the log odds of residential burglary increased by 0.01. In other words, the more a building is surveyed by passersby, the less likely it is that that building would be chosen for residential burglary. However, this effect size can be considered negligible.

Model 2 includes seven additional theoretically important variables: building use, diversity, maintenance, vacant lot, corner/middle lot, no-trespassing symbols and facing of buildings. The test of the full model against the constant only model was statistically significant (χ^2 (8) = 15.74, $p < 0.05$). According to the likelihood ratio test statistic, Model 2 was superior to Model 1 in terms of overall model fit. The H-L test (χ^2 (8) = 10.62, $p > 0.05$) suggested that the model was fit to the data well. However, the Nagelkerke R^2 value of 0.10 indicated that the model is not very accurate in predicting residential burglary. According to the model, after controlling for seven additional theoretically important independent variables, the significant contribution of the pedestrian surveillability variable to the model faded away (OR = 1.00; 95%CI = 0.99-1.01; $p > 0.05$).

Lastly, the area under the ROC curve for prediction of residential burglaries in relation to occupant surveillability gave a value of 0.41 (95%CI = 0.32-0.50; $p < 0.05$). This value showed that occupant surveillability is negatively associated with residential burglary, but the model is not accurate in classifying true positive events. The area under the ROC curve for prediction of residential burglary in relation to road surveillability gave a value of 0.61 (95%CI = 0.53-0.70; $p = 0.009$). This value showed that road surveillability is positively associated with residential burglary, but the model is not accurate in classifying true positive events. The area under the ROC curve for prediction of residential burglary in relation to pedestrian surveillability gave values of 0.57 (95%CI = 0.48-0.65; $p > 0.05$). This value showed that pedestrian surveillability model is neither significant nor accurate at classifying true positive events (See *Figure 80* and Table 93).

Table 90

Logistic regression analysis of 224 buildings for residential burglaries in relation to occupant' surveillability within 49 feet of buildings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	95% C.I. for Exp(B) Upper
Model 1								
Occupant surveillability 49 feet	-0.02	0.01	3.01	1	0.083	0.98	0.97	1.00
Constant	-0.50	0.30	2.81	1	0.094	0.61		

Model Evaluation	Block1	df	Sig.
Chi-square	3.23	1	0.072
-2 Log likelihood	261.04		
Cox and Snell (R square)	0.014		
Nagelkerke (R Square)	0.021		
Hosmer and Lemeshow Test (Chi-square)	14.00	8	0.082

Table 91

Logistic regression analysis of 224 buildings for residential burglaries in relation to road surveillability within 49 feet of buildings (Source: Author).

							95% C.I. for Exp(B)	
Independent and Control Variables	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Road surveillability 49 feet	0.04	0.01	8.15	1	0.004	1.04	1.01	1.06
Constant	-1.22	0.18	45.92	1	0.000	0.30		
Model 2								
Occupant surveillability 49 feet	0.04	0.02	4.72	1	0.030	1.04	1.00	1.08
Corner vs. middle lot (1 = Corner lot)	0.12	0.50	0.06	1	0.804	1.13	0.43	3.00
Building Use (1 = 2 plus units)	0.49	0.33	2.13	1	0.144	1.63	0.85	3.14
Presence of no-trespassing signs (1 = Yes)	0.73	0.44	2.75	1	0.097	2.07	0.88	4.90
Opening face (1 = Neighborhood collector)	0.68	0.37	3.35	1	0.067	1.97	0.95	4.07
Presence of facilities within 49 feet (1 = Yes)	-0.54	1.13	0.23	1	0.630	0.58	0.06	5.27
Adjacent vacant lot (1 = Yes)	0.72	0.64	1.26	1	0.261	2.05	0.59	7.14
Maintenance (1 = Maintained)	-0.18	0.32	0.33	1	0.565	0.83	0.45	1.55
Constant	-1.65	0.30	30.29	1	0.000	0.19		

Model Evaluation	Block1	df	Sig.	Block2	df	Sig.
Chi-square	8.36	1	0.004	20.33	8	0.009
-2 Log likelihood	255.92			243.94		
Cox and Snell (R square)	0.037			0.087		
Nagelkerke (R Square)	0.053			0.125		
Hosmer and Lemeshow Test (Chi-square)	4.22	5	0.518	11.34	7	0.125

Table 92

Logistic regression analysis of 224 buildings for residential burglaries in relation to pedestrian surveillability within 49 feet of buildings (Source: Author).

							95% C.I. for Exp(B)	
Independent and Control Variables	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Pedestrian surveillability 49 feet	0.01	0.00	4.42	1	0.036	1.01	1.00	1.01
Constant	-1.36	0.25	30.07	1	0.000	0.26		
Model 2								
Occupant surveillability 49 feet	0.00	0.01	0.39	1	0.530	1.00	0.99	1.01
Corner vs. middle lot (1 = Corner lot)	0.62	0.53	1.39	1	0.239	1.86	0.66	5.24
Building Use (1 = 2 plus units)	0.46	0.33	1.93	1	0.165	1.58	0.83	3.03
Presence of facilities within 49 feet (1 = Yes)	0.68	0.44	2.40	1	0.121	1.97	0.84	4.65
Presence of no-trespassing signs (1 = Yes)	0.61	0.37	2.74	1	0.098	1.84	0.89	3.78
Opening face (1 = Neighborhood collector)	-0.59	1.12	0.27	1	0.601	0.56	0.06	4.98
Adjacent vacant lot (1 = Yes)	0.66	0.63	1.09	1	0.296	1.94	0.56	6.71
Maintenance (1 = Maintained)	-0.15	0.31	0.24	1	0.623	0.86	0.46	1.58
Constant	-1.66	0.36	21.70	1	0.000	0.19		

Model Evaluation	Block1	df	Sig.	Block2	df	Sig.
Chi-square	4.37	1	0.037	15.74	8	0.046
-2 Log likelihood	259.91			248.53		
Cox and Snell (R square)	0.019			0.068		
Nagelkerke (R Square)	0.028			0.098		
Hosmer and Lemeshow Test (Chi-square)	10.09	8	0.259	10.62	8	0.224

Table 93

ROC statistics for residential burglaries in relation to occupant, road and pedestrian surveillability within 49 feet of buildings (Source: Author).

				95% C.I.	
Independent Variables	Area	S.E.	Sig.	Lower	Upper
Occupant surveillability 49 feet	0.41	0.05	0.041	0.32	0.50
Road surveillability 49 feet	0.61	0.04	0.009	0.53	0.70
Pedestrian surveillability 49 feet	0.57	0.05	0.123	0.48	0.65

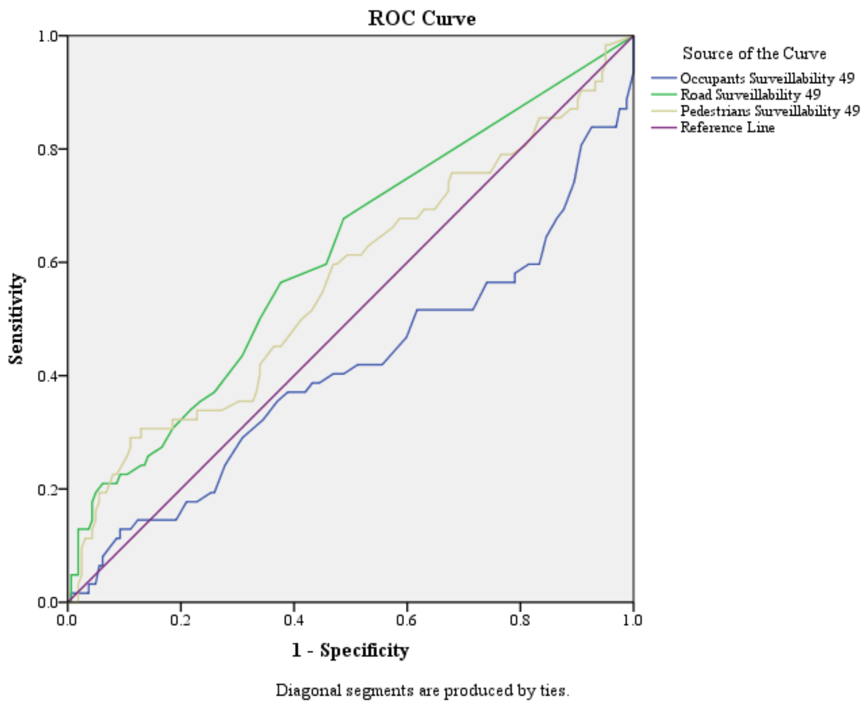


Figure 80. ROC curves for residential burglary in relation to occupant, road and pedestrian surveillability within 49 feet of buildings (Source: Author).

5.4.2.3.2 95 feet distance

Logistic regression analyses were performed to understand whether residential burglaries can be reliably predicted from knowledge of occupant, road and pedestrian surveillability. The test of the full model against the constant only model for the occupant surveillability model (χ^2 (1) = 0.04, p > 0.05), the road surveillability model (χ^2 (1) = 2.04, p > 0.05) and the pedestrian surveillability model (χ^2 (1) = 0.78, p > 0.05) were statistically insignificant (See Table 94, Table 95 and Table 96).

The area under the ROC curve for prediction of residential burglary in relation to pedestrian, road and pedestrian surveillability gave values of 0.45 (95%CI = 0.36-0.54; p > 0.05), 0.54 (95%CI = 0.45-0.64; p > 0.05) and 0.53 (95%CI = 0.44-0.62; p > 0.05) respectively. These values showed that the occupant, road and pedestrian surveillability models are neither significant nor accurate at classifying true positive events (See *Figure 81* and Table 97).

Table 94

Logistic regression analysis of 224 buildings for residential burglaries in relation to occupant surveillability within 95 feet of buildings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Model 1								
Occupant surveillability 95 feet	0.00	0.01	0.04	1	0.836	1.00	0.99	1.01
Constant	-1.01	0.28	12.86	1	0.000	0.36		

Model Evaluation	Block1	df	Sig.
Chi-square	0.04	1	0.836
-2 Log likelihood	264.23		
Cox and Snell (R square)	0.000		
Nagelkerke (R Square)	0.000		
Hosmer and Lemeshow Test (Chi-square)	12.16	8	0.144

Table 95

Logistic regression analysis of 224 buildings for residential burglaries in relation to road surveillability within 95 feet of buildings (Source: Author).

Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Model 1								
Road surveillability 95 feet	0.01	0.00	2.08	1	0.150	1.01	1.00	1.01
Constant	-1.33	0.30	19.26	1	0.000	0.26		

Model Evaluation	Block1	df	Sig.
Chi-square	2.04	1	0.153
-2 Log likelihood	262.23		
Cox and Snell (R square)	0.009		
Nagelkerke (R Square)	0.013		
Hosmer and Lemeshow Test (Chi-square)	7.07	8	0.529

Table 96

Logistic regression analysis of 224 buildings for residential burglaries in relation to pedestrian surveillability within 95 feet of buildings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Pedestrian surveillability 95 feet	0.00	0.00	0.79	1	0.373	1.00	1.00	1.00
Constant	-1.22	0.33	13.43	1	0.000	0.29		

Model Evaluation	Block1	df	Sig.
Chi-square	0.78	1	0.376
-2 Log likelihood	263.49		
Cox and Snell (R square)	0.003		
Nagelkerke (R Square)	0.005		
Hosmer and Lemeshow Test (Chi-square)	13.57	8	0.094

Table 97

ROC statistics for residential burglaries in relation to occupant, road and pedestrian surveillability within 95 feet of buildings (Source: Author).

Independent Variables	Area	S.E.	Sig.	95% C.I. Lower	95% C.I. Upper
Occupant surveillability 95 feet	0.45	0.05	0.220	0.36	0.54
Road surveillability 95 feet	0.54	0.05	0.299	0.45	0.64
Pedestrian surveillability 95 feet	0.53	0.05	0.482	0.44	0.62

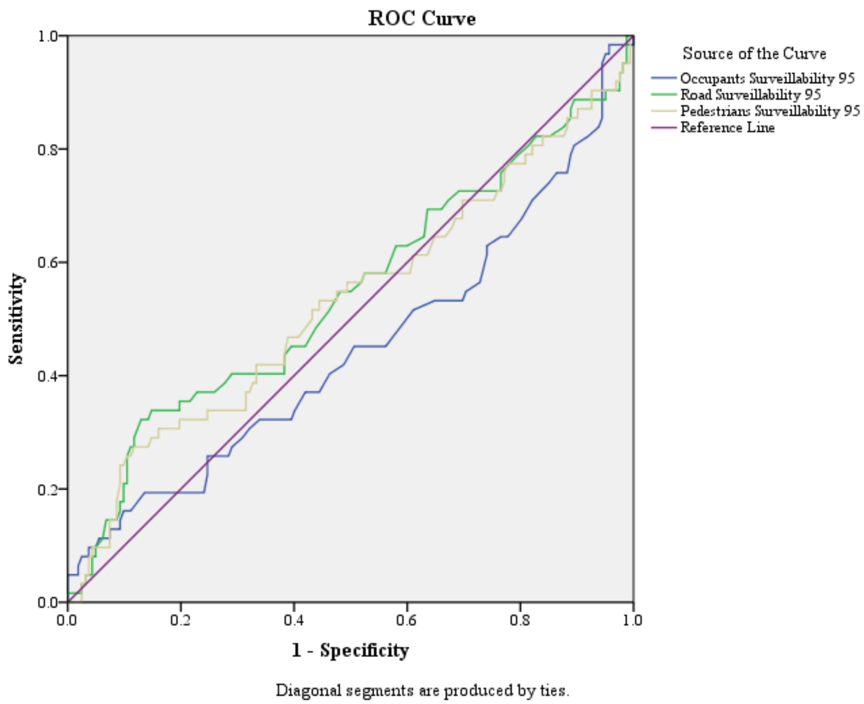


Figure 81. ROC curves for residential burglary in relation to occupant, road and pedestrian surveillability within 95 feet of buildings (Source: Author).

5.4.2.3.3 141 feet distance

Logistic regression analyses were performed to understand whether residential burglaries can be reliably predicted from knowledge of occupant, road and pedestrian surveillability. The test of the full model against the constant only model for the occupant surveillability model (χ^2 (1) = 3.37, $p > 0.05$), the road surveillability model (χ^2 (1) = 1.19, $p > 0.05$) and the pedestrian surveillability model (χ^2 (1) = 0.29, $p > 0.05$).were statistically insignificant (See Table 98, Table 99 and Table 100).

The area under the ROC curve for prediction of residential burglary in relation to occupant, road and pedestrian surveillability gave values of 0.42 (95%CI = 0.33-0.50; $p > 0.05$), 0.52 (95%CI = 0.43-0.62; $p > 0.05$) and 0.52 (95%CI = 0.43-0.61; $p > 0.05$) respectively. These values showed that the occupant, road and pedestrian surveillability models are neither significant nor accurate at classifying true positive events (See *Figure 82* and Table 101).

Table 98

Logistic regression analysis of 224 buildings for residential burglaries in relation to occupant surveillability within 141 feet of buildings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Occupant surveillability 141 feet	-0.01	0.00	3.20	1	0.073	0.99	0.99	1.00
Constant	-0.39	0.34	1.32	1	0.251	0.68		

Model Evaluation	Block1	df	Sig.
Chi-square	3.37	1	0.066
-2 Log likelihood	260.90		
Cox and Snell (R square)	0.015		
Nagelkerke (R Square)	0.022		
Hosmer and Lemeshow Test (Chi-square)	11.20	8	0.191

Table 99

Logistic regression analysis of 224 buildings for residential burglaries in relation to road surveillability within 141 feet of buildings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Road surveillability 141 feet	0.00	0.00	1.21	1	0.271	1.00	1.00	1.01
Constant	-1.24	0.30	17.32	1	0.000	0.29		

Model Evaluation	Block1	df	Sig.
Chi-square	1.19	1	0.275
-2 Log likelihood	263.08		
Cox and Snell (R square)	0.005		
Nagelkerke (R Square)	0.008		
Hosmer and Lemeshow Test (Chi-square)	20.05	8	0.010

Table 100

Logistic regression analysis of 224 buildings for residential burglaries in relation to pedestrian surveillability within 141 feet of buildings (Source: Author).

							95% C.I. for Exp(B)	
Independent Variable	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
Pedestrian surveillability 141 feet	0.00	0.00	0.29	1	0.591	1.00	1.00	1.00
Constant	-1.11	0.32	12.00	1	0.001	0.33		

Model Evaluation	Block1	df	Sig.
Chi-square	0.29	1	0.593
-2 Log likelihood	263.99		
Cox and Snell (R square)	0.001		
Nagelkerke (R Square)	0.002		
Hosmer and Lemeshow Test (Chi-square)	7.64	8	0.470

Table 101

ROC statistics for residential burglaries in relation to occupant, road and pedestrian surveillability within 141 feet of buildings (Source: Author).

				95% C.I.	
Independent Variables	Area	S.E.	Sig.	Lower	Upper
Occupant surveillability 141 feet	0.42	0.04	0.059	0.33	0.50
Road surveillability 141 feet	0.52	0.05	0.573	0.43	0.62
Pedestrian surveillability 141 feet	0.52	0.05	0.711	0.43	0.61

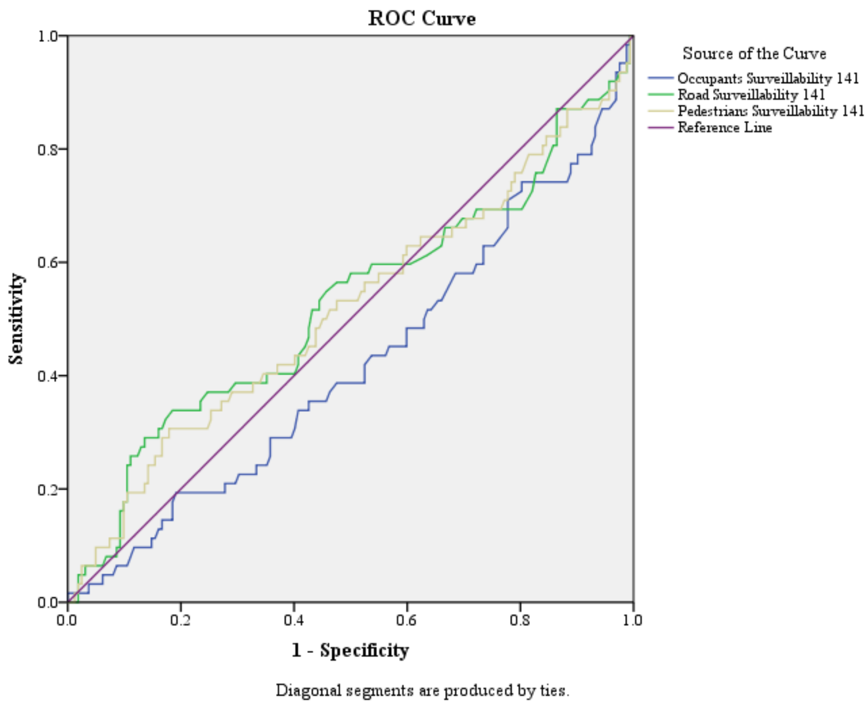


Figure 82. ROC curves for residential burglary in relation to occupant, road and pedestrian surveillability within 141 feet of buildings (Source: Author).

5.4.2.3.4 Binary logistic regression in summary

I conducted binary logistic regressions to make predictions regarding the most likely residential burglaries from the knowledge of occupant, road and pedestrian surveillability (See Table 102). The following hypothesis was proposed in the introductory chapter of this dissertation:

- A residential burglary can be reliably predicted from the knowledge of occupant, road and pedestrian surveillability.

The log of the odds of residential burglaries was positively related to road surveillability within 49 feet of buildings in univariate and multivariate analyses. The log of the odds of burglary commission in multivariate analysis was only significant for occupant surveillability within 49 feet of building openings. The log of the odds of residential burglaries was positively related to pedestrian surveillability within 49 feet of buildings in univariate analysis but I consider the effect size to be considered negligible.

In short, the Nagelkerke R^2 value of significant logistic regressions analyses ranged between 0.03 and 0.05 indicating that residential burglaries cannot be reliably predicted from knowledge of road or pedestrian surveillability. Nevertheless, road surveillability had a small effect in residential burglary.

Table 102

Logistic regression analysis of buildings for residential burglaries in relation to occupant, road and pedestrian surveillability within 49, 95 and 141 feet of buildings (Source: Author).

	49 feet				95 feet				141 feet			
Independent Variables	M1	Sig.	M2	Sig.	M1	Sig.	M2	Sig.	M1	Sig.	M2	Sig.
Occupant surveillability	0.98	0.083	---	---	1.00	0.836	---	---	0.99	0.073	---	---
Road surveillability	1.04	0.004	1.04	0.030	1.01	0.150	---	---	1.00	0.271	---	---
Pedestrian surveillability	1.01	0.036	1.00	0.530	1.00	0.373	---	---	1.00	0.591	---	---

Note: M1 stands for Exp(B) for model 1, and M2 stands for Exp(B) model 2.

5.5 Summary

I employed descriptive and inferential statistics to comprehend the relationship between natural surveillance and residential burglary commissions and residential burglaries. I can conclude the followings in light of the research questions and hypotheses set forth at the building opening level.

1. For building openings. There was a statistically significant inverse relationship between the degree of occupant surveillability and commission of residential burglaries within 49, 95 and 141 feet of building openings. No statistically significant relationship was observed between the degree of road and pedestrian surveillability and commission of residential burglaries.
2. For building openings. Burglarized building openings had statistically significant lower mean rank of occupant surveillability compared to non-burglarized building openings within 49, 95 and 141 feet of building openings. No statistically significant relationship was observed between the mean rank of road and pedestrian surveillability and commission of residential burglaries.
3. For building openings. A burglar's point of entry could not be reliably predicted from the knowledge of occupant, road and pedestrian surveillability. However, the log of the odds of burglary commission was negatively related to occupant surveillability within 49 and 95 feet of building openings, and positively related to road surveillability within 49 feet of building openings.

4. For door openings. There was a statistically significant direct relationship between the degree of road surveillability and burglary commission through doors within 49 feet of door openings. No statistically significant relationship was observed between the degree of occupant and pedestrian surveillability and burglary commission through door openings.
5. For door openings. Burglarized doors had statistically significant higher mean rank of road surveillability compared to non-burglarized doors within 49 feet of door openings. No statistically significant relationship was observed between the mean rank of occupant and pedestrian surveillability and burglary commission through door openings.
6. For door openings. Burglary commission through doors could not be reliably predicted from the knowledge of occupant, road and pedestrian surveillability. However, the log of the odds of burglary commission through doors was positively related to road surveillability within 49 feet of doors.
7. For window openings. There was a statistically significant inverse relationship between the degree of occupant surveillability and burglary commission through windows within 49 and 95 feet of window openings. No statistically significant relationship was observed between the degree of road and pedestrian surveillability and burglary commission through window openings.
8. For window openings. Burglarized windows had statistically significant lower mean rank of occupant surveillability compared to non-burglarized windows within 49 feet of window openings. No statistically significant relationship was observed between the mean rank of road and pedestrian surveillability and burglary commission through window openings.

9. For window openings. Burglary commission through windows could not be reliably predicted from the knowledge of occupant, road and pedestrian surveillability. However, the log of the odds of burglary commission through windows was negatively related to occupant surveillability within 49 and 95 feet of windows.
10. For buildings. There was a statistically significant inverse relationship between the degree of occupant surveillability and a statistically significant direct relationship between the degree of road surveillability and residential burglaries within 49 feet of building openings. No statistically significant relationship was observed between the degree of pedestrian surveillability and commission of residential burglaries.
11. For buildings. Burglarized building openings had statistically significant lower mean rank of occupant surveillability and statistically significant higher mean rank of road surveillability compared to non-burglarized buildings within 49 feet of buildings. No statistically significant relationship was observed between the mean rank of pedestrian surveillability and residential burglaries.
12. For buildings. A residential burglary could not be reliably predicted from the knowledge of occupant, road and pedestrian surveillability. However, the log of the odds of residential burglary was positively related to road surveillability within 49 feet of buildings.

6 DISCUSSION, IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

6.1 Introduction

This study is believed to be the only study extant to objectively quantify the notion of "eyes upon the street" in three dimensions, and to then compare the degree or intensity of natural surveillance with burglary occurrence. This chapter sheds light on the principal findings, potential implications and limitations of this study. Areas for future research are also presented.

6.2 Discussion

At the building opening level, the results revealed that burglary commission through building openings was significantly associated with lower degrees of occupant surveillability within all distance measures of surveillability. This finding is consistent with a previous study hypothesizing occupants surveillability to be related with vulnerability of houses to burglary (Brown & Altman, 1981).

When building openings were stratified into door and window openings, burglary commission through doors was significantly associated with higher degrees of road surveillability within 49 feet of door openings. I could not locate any study relating the degree of surveillability of doors to burglary commissions. This is one of the unique findings of this study.

Burglary commission through windows was significantly related to lower degrees of occupant surveillability within 49 and 95 feet of window openings. Even though I analyzed surveillability based on distance and not on street segment, this finding is consistent with previous work showing positive relationships between the degree of intervisibility between windows and burglary commissions (Van Nes & López, 2010).

Consistent with correlations, burglarized building openings were shown to have statistically significant lower mean rank of occupant surveillability compared to non-burglarized building openings within all distance measures of surveillability. After stratifying building openings to doors and windows, burglarized door openings were shown to have statistically significant higher mean rank of road surveillability compared to non-burglarized ones within 49 feet of doors. In addition, burglarized window openings were shown to have statistically significant lower mean rank of occupant surveillability compared to non-burglarized ones within 49 and 95 feet of windows. These findings are unique as other studies did not examine whether the degree of natural surveillance differs between burglarized and non-burglarized building openings.

This study showed that the log of the odds of burglary commission was negatively related to occupant surveillability within 49 and 95 feet of building openings, and positively related to road surveillability within 49 feet of building openings. After stratifying building openings to doors and windows, the log of the odds of burglary commission through doors was positively related to road surveillability within 49 feet of doors and the log of the odds of burglary commission through windows was negatively related to occupant surveillability within 49 and 95 feet of windows. These findings are also unique as other studies did not examine whether burglars point of entries can be delineated from the knowledge of natural surveillance.

Findings at the building opening level can be explained through the fact that generally placement of windows makes them more observable from and to other windows and placement of doors makes them more visible from and to roads. Therefore, the more door openings are surveyed by roads, it may be the case that they would be seen and chosen for a burglary commission. Further, the more window openings are surveyed by neighboring building openings, it may be the case that they might not be chosen for a burglary commission.

At the building level, the results revealed that burglary occurrence was significantly associated with lower degrees of occupant surveillability. This finding is consistent with previous studies hypothesizing or finding positive relationships between occupant surveillability and burglary occurrence (Brown & Altman, 1981; Brown & Altman, 1983; Coupe & Blake, 2006; Ham-Rowbottom et al., 1999; Macdonald & Gifford, 1989; K. T. Shaw & Gifford, 1994). In addition, the results of my study showed that burglary occurrence was significantly associated with higher degrees of road surveillability within 49 feet from buildings. This finding is in contrast with previous studies (Ham-Rowbottom et al., 1999; Macdonald & Gifford, 1989; Reynald, 2011a; K. T. Shaw & Gifford, 1994) showing significant inverse relationships between road surveillability and vulnerability of houses to burglary.

Consistent with correlations, burglarized dwellings were shown to have statistically significant lower mean rank of occupant surveillability and statistically significant higher mean rank of road surveillability compared to non-burglarized dwellings within 49 feet of buildings.

These findings are unique as other studies did not examine whether the degree of natural surveillance differs between burglarized and non-burglarized buildings.

The log of the odds of residential burglary occurrence was shown to be positively related to road surveillability within 49 feet of buildings. This finding is in contrast with a previous study showing residential burglary occurrence to be predicted from lower degrees of road surveillability (Ham-Rowbottom et al., 1999). This contradiction may have arisen because of methodological differences in quantifying surveillability between my study and Ham-Rowbottom et al. study. Ham-Rowbottom et al. defintion of road surveillability inlcuded some measurements related to occupant surveillability for quatification of road surveillability.

This study showed that once surveillability measures were aggregated, ambiguities in the relationship surveillability measures and burglary commissions that may call for further studies disappear. For instance, observed curvilinear relationships between some measures of surveillability and burglary commissions faded away once measures of natural surveillance were aggregated at the building level. This finding implies that aggregation may obscure important ambiguities that should be further addressed and studied. It also suggests that studying incidents at finer scales (here, building openings) is as important as more aggregate levels of study and analysis (here, building).

In addition, I would like to point out that observed insignificant relationships between some measures of surveillability (i.e. pedestrian, etc.) and burglary incidents does not necessarily mean that surveillability measures do not influence burglary commission or occurrence. Small sample size (a few number of geocoded burglaries) limited our ability to make inferences based on statistical significance. Furthermore, the results presented in the statistical chapter of this dissertation were computed without employing statistical techniques for rare events (i.e. Fishers exact test, etc.). Thereby, the magnitude of associations and the gained predictive power even though small shed light on the existence of a relationship between natural surveillance and burglary commissions. Moreover, findings of this study highlight the importance of the notion of natural surveillance even in low socio-economic high-criminogenic areas, even though results are specific to an area in the City of Spokane, WA. Thus, CPTED policies and practices may be applicable beyond socio-economic status and crime-prone standing of residential quarters.

6.3 Implications

Crime has different causes and criminals commit crimes for various reasons; therefore, creating safer societies is an effort which demands different prevention strategies and that transcends disciplinary boundaries (Tonry & Farrington, 1995). Evidence-based societies are societies with governmental policies and local practices grounded on interventions proven to be effective. In evidence-based societies, crime prevention policies and practices are established on the best possible evidence. Even though evidence-based interventions[25] have collected much attention in the healthcare sciences, evidence-based crime prevention and evidence-based design and planning are still in their infancy and have recently garnered some support and recognition (Lawrence W Sherman, 2003; Welsh & Farrington, 2001, 2005). The following sections discuss

[25] According to Petrosino (2000) "an evidence-based approach requires that the results of rigorous evaluation be rationally integrated into decisions about interventions by policymakers and practitioners alike" (p. 635).

potential implications of this research for creating evidence-based approaches to crime prevention.

6.3.1 For criminologists

Studying and developing predictive tools for forecasting crime in relation to characteristics of spatial design and configurations need precise and accurate data on locations and spatial characteristics of crime sites. Firstly, law enforcement agencies can benefit from advanced knowledge and technologies developed by geoscientists to more precisely collect data on locations of crimes. For instance, mapping of crime sites should be required to be GPS-based. GPS-based technologies can enhance abilities of law enforcement officers to map exact location of crimes, particularly in circumstances where conveying exact locations could be hard (i.e. entry point of burglaries, location of car theft, larceny theft, etc.). Secondly, appropriate procedures should be developed for collecting information on spatial characteristics of crime sites (i.e. security, etc.). That data should be required to be transcribed and considered as important as other variables transcribed in crime reports.

The tool developed in this study can be tested for delineating and predicting locations of other crimes with a spatial visibility component. For instance, this tool can be applied for studying locations of graffiti and car theft, among other crimes. In addition, visibility tools available in the ArcGIS platform can be applied to investigate locations from where shootings might have taken place or may take place. In addition, in organizing public speeches delivered by government officials, locations that provide visibility to podiums can be delineated in advance and secured. Furthermore, in case of traffic or collision analysis, precise locations of potential eyewitnesses who might provide valuable information for investigation of cases can be identified.

6.3.2 For architects and planners

Reducing crime requires a multi-agency partnership among different disciplines as diverse as design, planning, criminology, criminal justice and public policy (Armitage, 2007). Armitage, among others, elaborated on the difference between *control over crime opportunities* and the *responsibility for crime reduction* (p. 84), noting that the supply of crime opportunities is mostly influenced by agencies other than police departments (i.e. private housing developers, etc.); however, there is a duty placed on authorities (i.e. police departments, etc.) to advance strategic partnerships to deter crime and disorder within their area of influence. Separating the *supply* of and the *responsibility* for criminality exacerbated by minimal interaction between the federal, states and private sectors has posed difficulties for tackling crime and disorder also. Nevertheless, there exists a distinction between *reactive* and *proactive* actions (Reiss, 1971; Lawrence W. Sherman, In press). One way to implement the latter is to integrate environmental criminology concepts with design objectives at the early stages of project development (Armitage, 2007). An additional way to implement proactive crime prevention policies and practices is to incorporate crime-specific site analysis in subdivision and site plan review regulations (Rondeau, Brantingham, & Brantingham, 2005). Finally I suggest that architects and planners develop proactive strategies for the design of the United States cities by placing emphasis on systematic research and inquiry.

Katyal (2002) among others suggested that federal and state agencies in the United States can promote crime-control mechanisms through: (1) crime impact assessments for projects; and (2) reformation of building and zoning codes. Federal and state laws require submission of "Environmental Impact Assessment" for certain projects in order to file the effect of developments on the environment. Regulations should be passed requiring developers to submit "Crime Impact Assessment" for projects as well. In addition, in the United States, International Building Code (IBC) is applied for designing buildings. However, building codes still put an emphasis on fire safety and accessibility of buildings. The International Building Code should be revised to stress and incorporate crime prevention strategies. Another way to reinforce implementation of CPTED concepts in the design or planning of developments is to require architects and planners to familiarize themselves with principles of the first and second-generation CPTED.

The results of this study shed light on the importance of the notion of natural surveillance. Based on findings of this research, inward looking designs should be discouraged. In addition, to retain privacy and convey a feeling that natural surveillance is routinely taking place, one-way windows can be commercialized and more widely used in buildings. This way availability of blinds or lights may less influence burglars' judgments on whether residences are occupied or not. In addition, burglars may develop a feeling that there might be always someone watching and they may be detected, reported and arrested.

In addition, the methodology developed for quantification of natural surveillance in this dissertation can be applied to further understanding the threshold between providing residents with the ability to survey and intruding into residents' privacy through surveillance opportunities. This way building openings can be strategically placed taking into consideration not only safety but also privacy of building occupants. In addition, this tool can be employed to delineate where people with special needs or elderly adults who are more vulnerable may more safely reside.

From the technological point of view, Pictometry oblique aerial imagery is an invaluable resource for extracting information on architectural and landscape features on the surface of the earth. However, data extracted from Pictometry is less usable when buildings are constructed close to one another or when density of vegetation increases. In addition, reliability of data extracted from Pictometry imagery decreases if pictures are captured at timeframes when building facades are shadowed. Furthermore, it is hard to observe basement windows on Pictometry unless the resolution of images can be increased and pictures can be further magnified.

I also suggest that snapping be introduced to the measurements tool in the Pictometry retrieval system to increase the reliability of measurements extracted from Pictometry imagery. In addition, instead of five views (from north, south, east, west and top), more perspective imagery could be captured or produced to increase clarity on availability and dimensions of architectural and landscape features on the surface of the earth. Nevertheless, field observations or information from other resources may be still required to complement data extracted from oblique aerial imagery.

6.3.3 For residents of communities

As Felson (2006) hypothesized, well-supervised places might be unsuitable targets for outsider and insider delinquents. However, fairly well-supervised places might be considered unsuitable for outsider delinquents while insider delinquents can find the right moment for their offence. Thus, informal social control or how "… a community exerts pressure to prevent violation of its norms" (Murray, 1995, p. 351) plays an important role in the attractiveness of communities for criminals. Informal social control demands a fertile context and this context exists in socially cohesive neighborhoods. Social control denotes "… the capacity of a group to regulate its members according to desired principles- to realize collective, as opposed to forced, goals" (Sampson, Raudenbush, & Earls, 1997, p. 918). Communities are considered cohesive if residents use their capacity to regulate group level processes and respond to perceptible signs of social disorder. This mutual trust and solidarity influence the willingness of individuals to intervene for the common good and distinguish cohesive communities from disorganized societies (Sampson & Groves, 1989; Sampson et al., 1997). One way to limit criminal opportunities in residential settings is to encourage residents to be engaged in neighborhood watch activities. Another way to limit crime is to enhance natural surveillance opportunities through strategic placement of building openings.

It is also the case that buildings, certain other site elements and vegetation exist for long periods of time. Therefore, the management, redevelopment and maintenance of architectural and landscape features are concerns as important as their initial design and construction. And that management, redevelopment and maintenance can be reinforced by developing local, state and national rules and strengthened by residents of communities.

6.4 Limitations

As with most other crime forecasting studies, this study took an approach to forecast crime based on the past (also called post-casting). Burglary crime reports for a 5-year period between 2006 and 2010 have been read, and data on entry points of burglars were collected and georeferenced. Nevertheless, computing the degree of natural surveillance was based on oblique aerial imageries captured in year 2012. Even though the year each building was built or demolished was taken into consideration (one building has certainly been demolished in that time frame), I cannot tell whether minor changes were made to the placement of architectural and landscape features between the time of the crime and the current assessment, which could influence the degree of natural surveillance in this study.

In addition, visibility to and from dwellings varies during daylight and nighttime hours. It has been argued that during daylight hours, visibility from inside of buildings to outside is easier than surveillability from outside to inside of buildings (Ham-Rowbottom et al., 1999). In contrast during nighttime hours, it might be easier to survey inside of buildings from outside (when indoor lighting is on) than to observe outside from inside of buildings. However, the dependent variable for this study was binary indicating whether a building opening or building was burglarized or not. I was not able to create a dichotomous dependent variable (i.e. burglarized in daylight, burglarized in nighttime, burglarized in unknown hours and non-burglarized) for this study because of few number of burglaries in the study time frame.

Furthermore, I symbolized building openings with points placed on horizontal and vertical midpoint of building openings. I acknowledge the fact that symbolizing doors or windows with points influences surveillability. There might be instances in which the midpoint of a building opening could have been considered obstructed but some area of that building opening could still be observed by passersby being potential criminals.

Moreover, critics of the concept of natural surveillance claim that the ability to survey does not necessarily mean that surveillance is routinely taking place. However, conveying a feeling that one is constantly under observation not only discourages occurrence of criminal activities but also decreases the irrational fear associated with incidents of crime (Jacobs, 1961; Newman, 1973; Reynald, 2010). This research intended to establish a link between the degree of natural surveillance and commission of residential burglaries; however, it did not take into consideration whether and to what extent residents of the study area monitor the ongoing activities in their neighborhood. This study would however shed light on whether promoting more such surveillance by residents would be effective in reducing crime.

Lastly, research has shown observing crime does not necessarily lead to assisting individuals or properties being victimized. A number of conditions may intervene in observers' decisions to respond, including knowing the victims or vandalized/stolen properties, the ability to change the course of events, and the likelihood that the illegal activities taking place within the observers' area of influence (Newman, 1973), in addition to sense of responsibility, physical capability, availability of defense tools, incident severity and personal safety risks (Reynald, 2010). This study did not take into account whether people in the study area respond to criminal or delinquent activities when observed.

6.5 Future Research

More rigorous research is required to understand and develop a methodology for better comprehension and analysis of crimes with a natural surveillance component. Areas for future research may include:

- Study and compare the relationship between natural surveillance and crime (i.e. burglary commissions) in different SES status neighborhoods, in different urban forms and in different cultures;
- Test validity of my study findings by analyzing the relationship between natural surveillance and residential burglary commissions in a residential neighborhood representing similar SES and crime characteristics to the area chosen for this study;
- Include social-factors such as residence of ex-prisoners, location of families that constantly require social service, etc. in analysis;
- Test whether the model developed in this dissertation may be applicable for delineating locations of other crimes with a spatial visibility component (i.e. graffiti, car theft, shooting, etc.);
- Employ LiDAR data for quantifying the relationship between natural surveillance and burglary commissions at larger scales.

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Appendix A : SITE SELECTION

Research has shown that some key structural factors of communities are related to victimization rates. According to the classical view of social disorganization theory (C. R. Shaw & McKay, 1969), low economic status, ethnic heterogeneity and residential mobility explain variations in delinquency rates across communities. The contemporary view of the social disorganization theory (Sampson & Groves, 1989; Sampson et al., 1997) includes family disruption and weak social cohesion in addition to the above-mentioned factors for explaining variances in victimization rates across societies. Building on the contemporary view of social disorganization theory, structural factors of communities in the city of Spokane and residential burglary occurrence rates at the level of block group are gathered, analyzed and regressed leading to a multistage site selection procedure discussed in the flowing paragraphs.

A.1 Census Geography in the United States

Geographical units in United States are comprised of country, region, division, state, county, census tract, block group and census block (See *Figure 83*). The United States Census Bureau in Department of Commerce publishes information on structural factors of communities at different but not all geographical hierarchies. Block groups are the smallest territorial units for which the United States Census Bureau publishes information on some socio-economic characteristics of communities through American Community Survey (ACS). Block groups are areas with approximately between 600 and 3,000 inhabitants with an optimum size of 1,500 residents, nearly homogenous in social, demographic, economic and housing characteristics (Peters & MacDonald, 2004; United States Census Bureau, 2013).

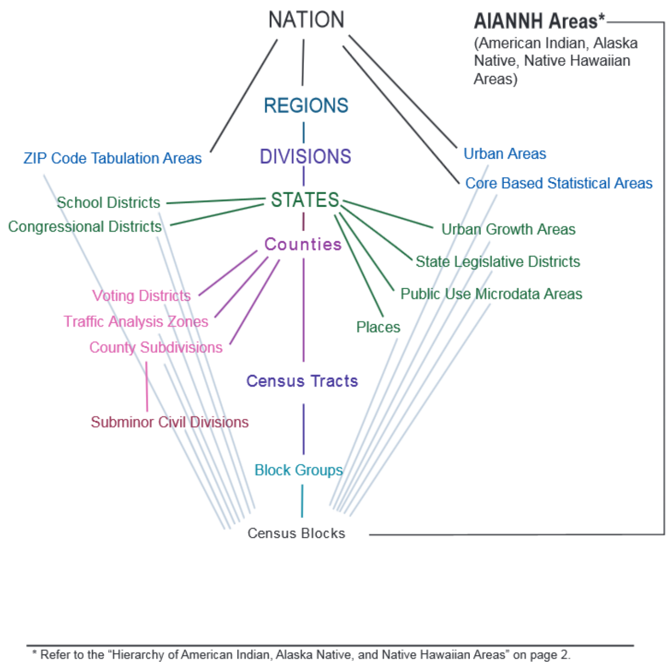

Figure 83. Standard hierarchy of census geographic entities. Retrieved from the United States Census Bureau: https://www.census.gov/geo/reference/hierarchy.html.

ACS files encompass information on geographies, estimates and margin of errors. American Community Survey data are estimates; therefore, some degree of error or uncertainty should be expected. Errors in ACS figures may occur as a result of sampling and/or non-sampling errors. Sampling error may arise due to the fact that the surveyed population may underrepresent or overrepresent characteristics of the actual population. Non-sampling errors may merge due to the employed procedures for collecting and processing data. Therefore, margin of error represents the range of uncertainty around estimates. A 90 percent confidence interval is used to represent the uncertainty in ACS estimated figures. This means there is a 90 percent chance that estimated values fall between their corresponding lower and upper confidence bounds. In general, smaller margin of errors represent greater precision of estimates and larger margin of errors show lower precisions. However, estimates and margin of errors should be considered simultaneously (American Community Survey Office, 2011a, 2011b).

A.2 The ACS 5-year Estimates and Residential Burglary Crime Data

The 2006-2010 ACS 5-year estimates were used for this research because the latest estimates released during the time this study were the 2006-2010 estimates. The technical documentation for the 2006-2010 ACS 5-year estimates provided detailed information on content, retrieval and use of ACS files (American Community Survey Office, 2011b). In addition, detailed tables showing table numbers and descriptions for demographic, social, economic and housing characteristics were available in this document. For this study, ACS data were retrieved via a macro-driven Excel spreadsheet downloaded from the American Community Survey's home page.[26] After tables were retrieved, abbreviated meaningful names were developed by for ACS field labels because the original ACS field labels had long names with line breaks making them inappropriate for use in the ArcGIS platform.

I next selected block groups from the Spokane County block group shapefile whose centroid was located inside the boundaries of the Spokane City (one selection was removed because crime data for this block group was not fully available). 166 block groups were exported as a new shapefile called "SpokaneCity_BlockGroup." I then used three fields named "LOGRECNO", "GEOID" and "GEOID10" for joining ACS data to the SpokaneCity_BlockGroup shapefiles. ACS estimates provided information on poverty and inequality, family structure, mobility and community change, and some other population and housing characteristics (See Table 103). Data on population, racial composition and ethnic

[26] The retrieval tool version 1.0.0.8 is used.

heterogeneity existed in Spokane County block group shapefile. Contrary to the estimate nature of ACS data, information provided in the georeferenced shapefile represented real figures.

Table 103

ACS data utilized for this study, tabulated by the author.

ACS Table #	ACS Table Title
B11001	Household type
B11005	Under 18 years by household type
B11012	Household type by tenure
B15002	Sex by educational attainment for the population 25 years and over
B16002	Household language by households
B17017	Poverty status
B17021	Poverty status of individuals in the past 12 months
B19001	Household income
B19056	Supplemental security income
B19057	Public assistance income
B23022	Sex by work status in the past 12 months
B25001	Housing units
B25002	Occupancy status
B25024	Units in structure
B25032	Tenure by units in structure
B25038	Tenure by year householder moved into unit
C07201	Mobility

Lastly, I calculated residential burglary crime rates for block groups during a time period close to 2006-2010. The City of Spokane provided crime point shapefiles for years 2008, 2009 and 2010 (City of Spokane, 2013). To calculate residential burglary crime rates, I first calculated the count of residential burglaries for years 2008, 2009 and 2010 followed by sum total of residential burglaries during this timeframe.[27] Next, residential burglary crime rates for block

[27] Majority of studies use population as the proper offence denominator for calculating rates of residential burglaries (Bellair, 2000), however some other research suggest the appropriate denominator should have been number of households (Wikström, 1991).

groups were calculated by dividing the number of residential burglaries to the population of block groups multiplied by 1000.

A.3 Socioeconomic Characteristics Regressed on Residential Burglaries

The relative strength and direction of a relationship between variables is explained by correlation. When predictions based on variables' relationships is the purpose of studies regression is utilized (Portney & Watkins, 2009). In a multiple regression, the regression coefficient displays the expected increase in the dependent variable by one unit increase in one of the independent variables holding all the other independent variables constant.

The outcome of regression analysis can be seriously influenced by outliers. Therefore, data are required to be screened for deviant scores before regression is conducted. Cases with extreme scores on one or combinations of variables, distorting the conclusions drawn from data, are considered outliers. Deviant scores might be errors in data entry, measurement, equipment failure or miscalculation or they can also be true representatives of the population for which the sample is intended (Mertler & Vannatta, 2005; Portney & Watkins, 2009). Some research suggests that values beyond three standard deviation from the mean are considered outliers (Portney & Watkins, 2009). Other research hypothesized that as the sample size increases, scores beyond four standard deviation from the mean should be considered outliers (Mertler & Vannatta, 2005). However, it is researcher's decision whether to retain or discard outliers from the analysis, and the decision is contingent upon a "thorough evaluation of the experimental conditions, the data collection procedures and the data themselves" (Portney & Watkins, 2009, p.

551). No statistical rationale exists for removing outliers as long as a causal factor unique to an outlier is not identified.

In order to predict how much of the variance in residential burglary crime rates could be explained by socio-economic characteristics of block groups, socio-economic characteristics were regressed on residential burglary crime rates.[28] First, the SPSS explore procedure was conducted to identify missing values and outliers and to evaluate normality of independent and dependent variables. No missing values were observed. However, visual inspection of the histogram and assessment of skeweness and kurtosis values indicated distributions of IVs (socio-economic characteristics of block groups) and the DV (burglary crime rates) were not normal. Research suggests different techniques to adjust for skewed distributions; one can be named as transforming values to their representative fractional ranks. Employing this technique, each case is given a value between 0 and 1.

Pearson's correlation coefficients were then computed to assess the relationship between socio-economic characteristics of block groups and residential burglary crime rates. Out of 67 variables, 48 were found to be significantly related to residential burglary crime rates, leaving 19 variables to have no relationship with rates of residential burglaries (See Table 104).

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[28] Descriptive and inferential statistical analyses for section of the study were carried out in IBM® SPSS® Statistics Premium GradPack (Student Version 20) in the windows environment, with alpha or level of significance for inferential statistics set at 0.05.

Table 104

Pearson's correlation coefficients for model variables (Source: Author).

IV	coeff	sig	IV	coeff	sig	IV	coeff	sig
Black	0.617	0.000	@1Detached	-0.504	0.000	Less10_000	0.488	0.000
Hispanic	0.421	0.000	@1Attached	0.251	0.001	@10_14999	0.477	0.000
			@2_4Units	0.519	0.000	@15_19999	0.310	0.000
MCHH	-0.542	0.000	@5_9Units	0.340	0.000	@20_24999	0.209	0.007
MHH	0.061	0.435	@10_19Units	0.250	0.001	@25_29999	0.219	0.005
FHH	0.220	0.004	@20_49Units	0.238	0.002	@30_34999	0.133	0.088
NFHH	0.330	0.000	@50_UpUnits	0.116	0.137	@35_39999	-0.004	0.957
						@40_44999	0.031	0.695
HHwith18	-0.103	0.188	HUOccupied	-0.587	0.000	@45_49999	-0.086	0.268
HH18MC	-0.383	0.000	HUVacant	0.587	0.000	@50_59999	-0.087	0.263
HH18M	0.002	0.978				@60_74999	-0.374	0.000
HH18F	0.234	0.002	HUOwner	-0.579	0.000	@75_99999	-0.494	0.000
HH18NF	0.151	0.052	HURenter	0.579	0.000	@100_124999	-0.340	0.000
						@125_149999	-0.376	0.000
MCIncAPov18	-0.399	0.000	OwnerA2005	-0.262	0.001	@150_199999	-0.271	0.000
MCIncBPo18	0.234	0.002	RentA2005	0.447	0.000	@200000More	-0.336	0.000
MIncAPov18	-0.016	0.837						
MIncBPo18	0.126	0.106	MCHHOwnHU	-0.586	0.000	HousDensit	0.340	0.000
FIncAPov18	-0.011	0.885	MCHHRenHU	0.160	0.040	PopDensity	0.245	0.001
FIncBPov18	0.446	0.000						
			NFHHOwnHU	-0.258	0.001	Linguistic	0.240	0.002
HHIncBPov	0.641	0.000	NFHHRenHU	0.495	0.000			
HHwPAInco	0.441	0.000						
HHwSSInco	0.403	0.000	FHHRenHU	0.353	0.000			
			FHHOwnHU	-0.129	0.097			
NoEducation	0.051	0.515						
@1_8Grade	0.257	0.001	MHHRenHU	0.069	0.376			
@9_12Grade	0.528	0.000	MHHOwnHU	-0.060	0.440			
Unemployed	0.439	0.000						
@1_14hrsWork	-0.131	0.093						
@15-34hrsWork	0.014	0.854						
@35UphrsWork	-0.371	0.000						

A linear stepwise regression analysis was then conducted with socio-economic characteristics of block groups as independent variables and residential burglary crime rate as the dependent variable to identify which factors significantly predict rates of residential burglary in the city of Spokane. Variables significantly associated with increases in residential burglary crime rates were entered into the model. In addition, Pearson correlation coefficient values were utilized to determine the order in which independent variables were entered into the regression model, meaning that variables with higher correlation coefficients were entered first followed by factors with lower correlation coefficients.

Conducting a stepwise linear regression, no multi-collinearity was observed among the independent variables as tolerance statistics exceeded 0.1 for all of the variables, and VIFs did not exceed 10 meaning that variables are not correlated. Results of the linear stepwise regression revealed that the model significantly predicts residential burglary crime rates ($R^2 = 0.77$, $R^2adj = 0.598$, $F (4,161) = 59.92$, $p < 0.001$), accounting for 59.8% of the variance in residential burglaries. The review of p values in the table of coefficients showed four variables, percent of black population ($\beta = 0.249$, $t (161) = 3.881$, $p < 0.001$); percent of households with income below poverty ($\beta = 0.218$, $t (161) = 3.090$, $p < 0.001$); percent of vacant housing units ($\beta = 0.280$, $t (161) = 4.398$, $p < 0.001$); and percent of population with educational attainment of 9-12th grade ($\beta = 0.266$, $t (161) = 4.634$, $p < 0.001$) significantly contributed to the model and predicted rates of residential burglaries (See Table 105).

Table 105

Results of multiple regressions analysis (Source: Author).

Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.641[a]	.411	.408	.2228640	.411	114.503	1	164	.000
2	.711[b]	.506	.500	.2047942	.095	31.218	1	163	.000
3	.742[c]	.550	.542	.1960416	.044	15.880	1	162	.000
4	.773[d]	.598	.588	.1858036	.048	19.345	1	161	.000

a. Predictors: (Constant), Fractional Rank of HHIncBPov

b. Predictors: (Constant), Fractional Rank of HHIncBPov, Fractional Rank of Black

c. Predictors: (Constant), Fractional Rank of HHIncBPov, Fractional Rank of Black, Fractional Rank of @9_12Grade

d. Predictors: (Constant), Fractional Rank of HHIncBPov, Fractional Rank of Black, Fractional Rank of @9_12Grade, Fractional Rank of HUVacant

e. Dependent Variable: Fractional Rank of BurRate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.687	1	5.687	114.503	.000[b]
	Residual	8.146	164	.050		
	Total	13.833	165			
2	Regression	6.996	2	3.498	83.409	.000[c]
	Residual	6.836	163	.042		
	Total	13.833	165			
3	Regression	7.607	3	2.536	65.975	.000[d]
	Residual	6.226	162	.038		
	Total	13.833	165			
4	Regression	8.275	4	2.069	59.921	.000[e]
	Residual	5.558	161	.035		
	Total	13.833	165			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.180	.035		5.193	.000					
	Fractional Rank of HHIncBPov	.641	.060	.641	10.701	.000	.641	.641	.641	1.000	1.000
2	(Constant)	.099	.035		2.827	.005					
	Fractional Rank of HHIncBPov	.429	.067	.429	6.416	.000	.641	.449	.353	.678	1.475
	Fractional Rank of Black	.374	.067	.374	5.587	.000	.617	.401	.308	.678	1.475
3	(Constant)	.044	.036		1.218	.225					
	Fractional Rank of HHIncBPov	.358	.066	.358	5.383	.000	.641	.390	.284	.629	1.590
	Fractional Rank of Black	.314	.066	.314	4.778	.000	.617	.351	.252	.643	1.556
	Fractional Rank of @9_12Grade	.240	.060	.240	3.985	.000	.528	.299	.210	.767	1.305
4	(Constant)	-.007	.036		-.181	.856					
	Fractional Rank of HHIncBPov	.218	.071	.218	3.090	.002	.641	.237	.154	.501	1.995
	Fractional Rank of Black	.249	.064	.249	3.881	.000	.617	.292	.194	.608	1.645
	Fractional Rank of @9_12Grade	.266	.057	.266	4.634	.000	.528	.343	.232	.758	1.319
	Fractional Rank of HUVacant	.280	.064	.280	4.398	.000	.587	.328	.220	.614	1.628

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.045887	.941575	.503012	.2239398	166
Residual	-.5380840	.5685706	0E-7	.1835377	166
Std. Predicted Value	-2.041	1.958	.000	1.000	166
Std. Residual	-2.896	3.060	.000	.988	166

Assuming that not more than 59.8% of the variance in residential burglary rates could be explained by socioeconomic variables, even in low socioeconomic-high criminogenic areas some other variables such as characteristics of spatial design and configuration may encourage or prevent crime occurrence. Thus, in the final step, four factors contributing to rates of residential burglaries and residential burglary crime rates were copied to a new Microsoft Excel sheet. I first ranked our spreadsheet according to highest to lowest rates of burglary crime. I next selected a block group with high crime rates during a 3 year period between 2008 and 2010 with the significant independent variables from the regression model having values greater than their mean. The third neighborhood from the list provided in Table 106 is chosen because the first and second neighborhoods were mainly commercial-residential or industrial-residential neighborhoods and non-residential facilities constitute neatly half or more than half of the block group area.

Table 106

Block groups and their corresponding crime rate, percent of black population, percent of households with income below poverty, percent of vacant housing units and percent of population with educational attainment of 9-12th grade. Variables having values greater than their mean were given a value of 1or 1000 (Source: Author).

GEOID10	RatioBlack	HIncBPov	HUVac	9_12Grade	BurRate	RatioBlack	HIncBPov	HUVac	9_12Grade	BurRate
530630145003	0.05	0.34	0.10	0.19	75.09	1	1	1	1	1000
530630002003	0.03	0.39	0.09	0.09	65.70	1	1	1	1	1000
530630023001	0.05	0.49	0.12	0.16	62.38	1	1	1	1	1000
530630145001	0.06	0.49	0.15	0.02	59.32	1	1	1	0	1000
530630025005	0.04	0.50	0.13	0.20	53.69	1	1	1	1	1000
530630020004	0.03	0.49	0.10	0.13	52.57	1	1	1	1	1000
530630020003	0.04	0.49	0.10	0.17	51.80	1	1	1	1	1000
530630024002	0.04	0.23	0.11	0.06	48.51	1	1	1	0	1000
530630040005	0.04	0.40	0.18	0.12	46.25	1	1	1	1	1000
530630018001	0.05	0.35	0.13	0.06	46.19	1	1	1	0	1000
530630023002	0.03	0.13	0.12	0.22	44.70	1	0	1	1	1000
530630145002	0.05	0.16	0.23	0.19	44.42	1	0	1	1	1000
530630020005	0.02	0.13	0.10	0.06	42.79	0	0	1	0	1000
530630035002	0.07	0.62	0.07	0.09	41.51	1	1	1	1	1000
530630030001	0.08	0.40	0.04	0.21	41.11	1	1	0	1	1000
530630025006	0.03	0.32	0.11	0.00	40.67	1	1	1	0	1000
530630031003	0.04	0.27	0.12	0.22	40.55	1	1	1	1	1000
530630040001	0.06	0.24	0.11	0.07	38.91	1	1	1	1	1000
530630021001	0.02	0.29	0.08	0.05	37.92	0	1	1	0	1000
530630014003	0.01	0.28	0.09	0.12	36.65	0	1	1	1	1000
530630016002	0.03	0.38	0.07	0.16	34.18	1	1	0	1	1000
530630003002	0.04	0.07	0.07	0.07	34.10	1	0	0	1	1000
530630111022	0.01	0.25	0.07	0.10	34.01	0	1	1	1	1000
530630015003	0.03	0.40	0.08	0.22	33.97	1	1	1	1	1000
530630023003	0.03	0.30	0.09	0.16	33.70	1	1	1	1	1000
530630032003	0.01	0.18	0.21	0.02	33.39	0	1	1	0	1000

530630032001	0.02	0.21	0.15	0.13	32.93	1	1	1	1	1000
530630026003	0.05	0.16	0.06	0.08	32.64	1	0	0	1	1000
530630015004	0.03	0.08	0.07	0.04	32.41	1	0	0	0	1000
530630031001	0.10	0.46	0.07	0.05	32.26	1	1	1	0	1000
530630025002	0.04	0.34	0.07	0.12	32.09	1	1	1	1	1000
530630026004	0.04	0.14	0.06	0.22	31.11	1	0	0	1	1000
530630036001	0.04	0.25	0.11	0.06	31.08	1	1	1	0	1000
530630032004	0.02	0.15	0.20	0.05	30.36	0	0	1	0	1000
530630038001	0.03	0.14	0.10	0.15	30.22	1	0	1	1	1000
530630013002	0.03	0.19	0.07	0.12	30.20	1	1	1	1	1000
530630144001	0.03	0.59	0.13	0.19	29.95	1	1	1	1	1000
530630040002	0.03	0.07	0.08	0.09	29.85	1	0	1	1	1000
530630021002	0.02	0.19	0.06	0.00	29.66	0	1	0	0	1000
530630018002	0.03	0.28	0.07	0.03	29.33	1	1	0	0	1000
530630111011	0.02	0.33	0.09	0.18	29.11	1	1	1	1	1000
530630004003	0.04	0.36	0.08	0.07	28.96	1	1	1	1	1000
530630005003	0.01	0.16	0.04	0.05	28.75	0	0	0	0	1000
530630002004	0.02	0.18	0.09	0.05	28.54	1	0	1	0	1000
530630025001	0.05	0.17	0.11	0.00	28.22	1	0	1	0	1000
530630023004	0.04	0.32	0.06	0.04	28.14	1	1	0	0	1000
530630014001	0.02	0.11	0.06	0.21	28.04	0	0	0	1	1000
530630035001	0.02	0.40	0.29	0.05	27.89	1	1	1	0	1000
530630002001	0.01	0.41	0.05	0.24	27.78	0	1	0	1	1000
530630014004	0.03	0.21	0.08	0.04	27.41	1	1	1	0	1000
530630025003	0.02	0.51	0.08	0.09	27.35	0	1	1	1	1000
530630026002	0.06	0.34	0.08	0.10	27.34	1	1	1	1	1000
530630044001	0.02	0.12	0.08	0.03	27.22	0	0	1	0	1000
530630040004	0.03	0.24	0.09	0.03	26.96	1	1	1	0	1000
530630003003	0.04	0.20	0.07	0.13	26.64	1	1	0	1	1000
530630003004	0.02	0.04	0.07	0.11	26.63	0	0	0	1	1000
530630030002	0.07	0.30	0.09	0.12	26.10	1	1	1	1	1000
530630004001	0.02	0.16	0.05	0.10	25.96	1	0	0	1	1000
530630013001	0.02	0.14	0.05	0.05	25.94	1	0	0	0	1000

530630014002	0.03	0.15	0.07	0.12	25.88	1	0	0	1	1000
530630020002	0.02	0.16	0.09	0.08	25.82	0	0	1	1	1000
530630036004	0.01	0.28	0.15	0.04	25.64	0	1	1	0	1000
530630019001	0.02	0.16	0.08	0.04	25.64	0	0	1	0	1000
530630042003	0.00	0.05	0.02	0.00	25.12	0	0	0	0	1000
530630043002	0.01	0.00	0.02	0.00	24.39	0	0	0	0	1000
530630007001	0.01	0.08	0.05	0.07	24.25	0	0	0	0	1000
530630019003	0.02	0.16	0.07	0.14	24.07	0	0	0	1	1000
530630024001	0.05	0.28	0.14	0.20	23.74	1	1	1	1	1000
530630036003	0.02	0.19	0.11	0.02	23.70	1	1	1	0	1000
530630003001	0.01	0.08	0.04	0.13	23.60	0	0	0	1	1000
530630026001	0.04	0.27	0.06	0.04	23.10	1	1	0	0	0
530630046013	0.02	0.20	0.11	0.08	22.90	1	1	1	1	0
530630004002	0.02	0.27	0.05	0.11	22.88	0	1	0	1	0
530630006002	0.01	0.06	0.04	0.06	22.82	0	0	0	0	0
530630029001	0.03	0.12	0.04	0.12	22.62	1	0	0	1	0
530630047004	0.03	0.14	0.07	0.07	22.58	1	0	1	0	0
530630020001	0.02	0.19	0.07	0.03	22.53	0	1	0	0	0
530630015005	0.03	0.34	0.06	0.12	21.90	1	1	0	1	0
530630006001	0.01	0.23	0.06	0.05	21.41	0	1	0	0	0
530630044003	0.00	0.02	0.05	0.03	21.37	0	0	0	0	0
530630047002	0.03	0.10	0.05	0.06	21.29	1	0	0	0	0
530630002002	0.03	0.35	0.18	0.09	20.69	1	1	1	1	0
530630032002	0.03	0.28	0.12	0.03	20.22	1	1	1	0	0
530630005002	0.01	0.12	0.04	0.07	20.18	0	0	0	0	0
530630144004	0.02	0.02	0.03	0.09	19.98	0	0	0	1	0
530630009005	0.01	0.15	0.06	0.10	19.92	0	0	0	1	0
530630016003	0.02	0.21	0.03	0.09	19.67	0	1	0	1	0
530630041001	0.01	0.12	0.10	0.06	19.20	0	0	1	0	0
530630012002	0.02	0.08	0.04	0.02	19.15	0	0	0	0	0
530630111013	0.01	0.04	0.04	0.06	19.09	0	0	0	0	0
530630111012	0.02	0.19	0.08	0.07	19.00	0	1	1	0	0
530630011003	0.01	0.03	0.04	0.08	18.98	0	0	0	1	0

530630048002	0.01	0.07	0.09	0.06	18.97	0	0	1	0	0
530630007003	0.03	0.10	0.04	0.11	18.89	1	0	0	1	0
530630047001	0.03	0.28	0.06	0.09	18.87	1	1	0	1	0
530630031004	0.01	0.13	0.08	0.02	18.79	0	0	1	0	0
530630111021	0.02	0.11	0.07	0.05	18.71	0	0	0	0	0
530630038002	0.03	0.13	0.10	0.04	18.66	1	0	1	0	0
530630006003	0.01	0.10	0.03	0.10	18.66	0	0	0	1	0
530630009004	0.01	0.06	0.04	0.04	18.24	0	0	0	0	0
530630016001	0.02	0.48	0.04	0.13	17.96	1	1	0	1	0
530630015001	0.02	0.17	0.06	0.08	17.37	0	0	0	1	0
530630012001	0.01	0.20	0.06	0.11	17.37	0	1	0	1	0
530630046011	0.02	0.16	0.05	0.03	17.25	0	0	0	0	0
530630042004	0.01	0.00	0.04	0.01	17.05	0	0	0	0	0
530630019002	0.02	0.12	0.07	0.08	17.04	0	0	0	1	0
530630046012	0.02	0.07	0.05	0.05	16.78	0	0	0	0	0
530630044002	0.00	0.13	0.04	0.02	16.75	0	0	0	0	0
530630112013	0.01	0.13	0.09	0.07	16.45	0	0	1	1	0
530630005001	0.02	0.12	0.06	0.04	16.41	0	0	0	0	0
530630029003	0.03	0.06	0.04	0.14	16.39	1	0	0	1	0
530630045001	0.01	0.02	0.06	0.01	16.33	0	0	0	0	0
530630040003	0.02	0.08	0.05	0.00	16.20	0	0	0	0	0
530630039002	0.01	0.10	0.08	0.06	16.13	0	0	1	0	0
530630036002	0.01	0.59	0.08	0.00	15.38	0	1	1	0	0
530630013003	0.02	0.30	0.05	0.03	15.34	0	1	0	0	0
530630043001	0.03	0.18	0.05	0.02	15.24	1	0	0	0	0
530630041002	0.02	0.06	0.07	0.02	15.01	0	0	0	0	0
530630015002	0.01	0.18	0.05	0.08	14.85	0	1	0	1	0
530630144003	0.02	0.10	0.03	0.15	14.79	0	0	0	1	0
530630010002	0.01	0.00	0.04	0.07	14.67	0	0	0	0	0
530630046022	0.02	0.00	0.04	0.06	14.58	0	0	0	0	0
530630011002	0.01	0.02	0.04	0.01	13.88	0	0	0	0	0
530630007005	0.01	0.13	0.03	0.04	13.82	0	0	0	0	0
530630009001	0.01	0.29	0.04	0.12	13.81	0	1	0	1	0

530630010001	0.01	0.04	0.05	0.06	13.71	0	0	0	0	0
530630009002	0.00	0.04	0.05	0.00	13.62	0	0	0	0	0
530630011001	0.02	0.11	0.06	0.04	13.38	0	0	0	0	0
530630039001	0.00	0.19	0.11	0.08	13.25	0	1	1	1	0
530630010006	0.01	0.07	0.05	0.10	13.19	0	0	0	1	0
530630010003	0.01	0.04	0.05	0.02	13.14	0	0	0	0	0
530630009003	0.01	0.00	0.04	0.03	13.03	0	0	0	0	0
530630007006	0.02	0.05	0.04	0.00	12.89	0	0	0	0	0
530630144002	0.01	0.13	0.04	0.14	12.61	0	0	0	1	0
530630042002	0.01	0.07	0.03	0.05	12.43	0	0	0	0	0
530630007004	0.02	0.05	0.06	0.00	12.35	1	0	0	0	0
530630002005	0.02	0.07	0.05	0.02	12.29	1	0	0	0	0
530630031002	0.02	0.13	0.06	0.02	12.26	0	0	0	0	0
530630008002	0.01	0.07	0.04	0.01	11.99	0	0	0	0	0
530630045002	0.00	0.02	0.07	0.00	11.90	0	0	0	0	0
530630046021	0.02	0.10	0.05	0.06	11.89	1	0	0	0	0
530630042005	0.01	0.06	0.04	0.01	11.51	0	0	0	0	0
530630008001	0.01	0.07	0.05	0.04	11.47	0	0	0	0	0
530630029002	0.05	0.03	0.05	0.03	11.02	1	0	0	0	0
530630045003	0.00	0.02	0.05	0.01	11.00	0	0	0	0	0
530630043003	0.01	0.03	0.03	0.01	11.00	0	0	0	0	0
530630049003	0.01	0.00	0.05	0.01	10.82	0	0	0	0	0
530630007002	0.01	0.00	0.04	0.10	10.75	0	0	0	1	0
530630047003	0.01	0.02	0.06	0.00	10.75	0	0	0	0	0
530630048001	0.02	0.05	0.06	0.04	10.70	1	0	0	0	0
530630044004	0.01	0.05	0.05	0.06	10.53	0	0	0	0	0
530630041003	0.00	0.04	0.10	0.00	10.17	0	0	1	0	0
530630010005	0.00	0.07	0.05	0.02	10.09	0	0	0	0	0
530630009006	0.01	0.11	0.04	0.05	10.09	0	0	0	0	0
530630111014	0.02	0.21	0.15	0.03	9.55	0	1	1	0	0
530630049002	0.03	0.13	0.04	0.01	8.76	1	0	0	0	0
530630046023	0.02	0.09	0.03	0.03	8.46	1	0	0	0	0
530630042001	0.01	0.12	0.05	0.00	8.26	0	0	0	0	0

530630010004	0.02	0.04	0.02	0.00	7.19	0	0	0	0	0
530630106011	0.01	0.02	0.02	0.00	6.63	0	0	0	0	0
530630106022	0.00	0.00	0.03	0.03	6.46	0	0	0	0	0
530630106023	0.01	0.09	0.02	0.05	5.95	0	0	0	0	0
530630106021	0.01	0.02	0.08	0.03	5.67	0	0	1	0	0
530630025004	0.01	0.87	0.06	0.00	5.21	0	1	0	0	0
530630106024	0.01	0.02	0.02	0.00	4.54	0	0	0	0	0
530630112011	0.02	0.10	0.08	0.00	4.33	0	0	1	0	0

APPENDIX B: DRAWINGS AND SKETCHES

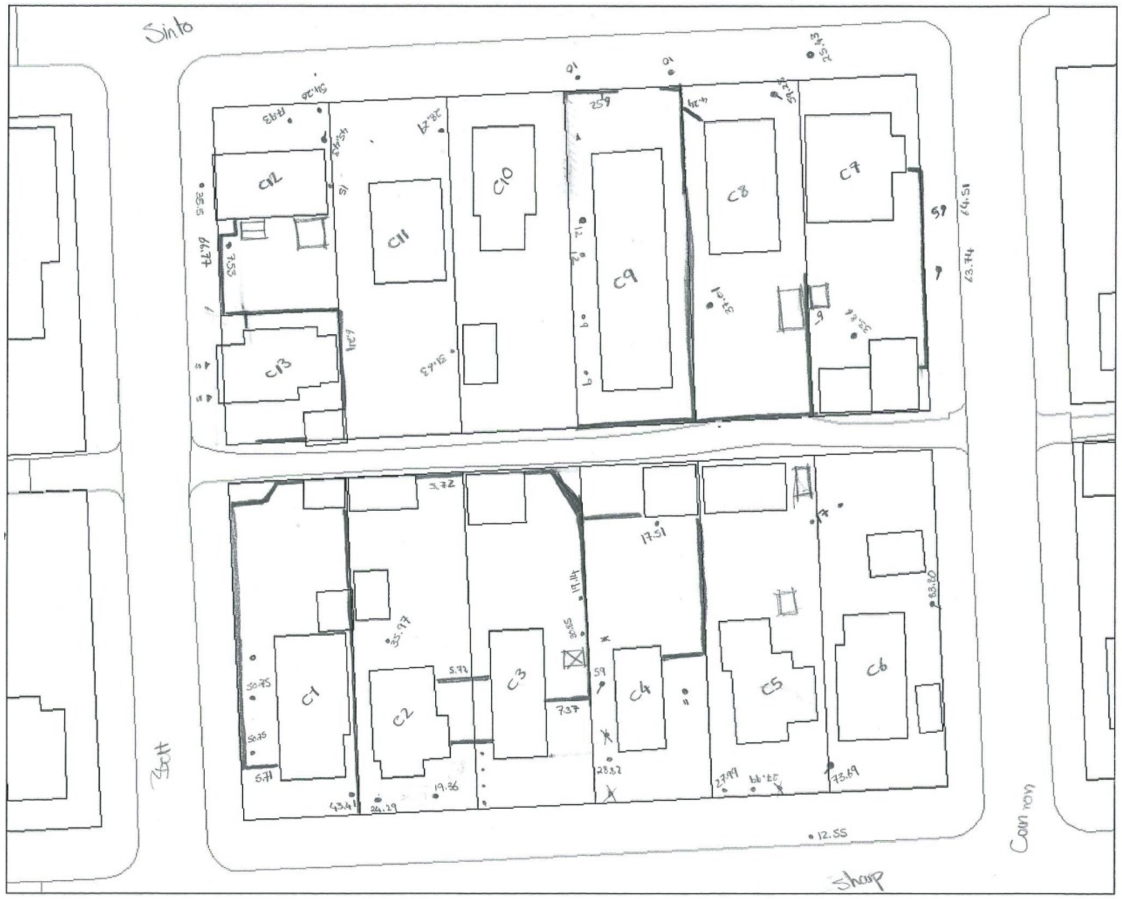

Figure 84. Example of sheets used for recording information on location, height and type of vegetation and barrier features (Source: Author).

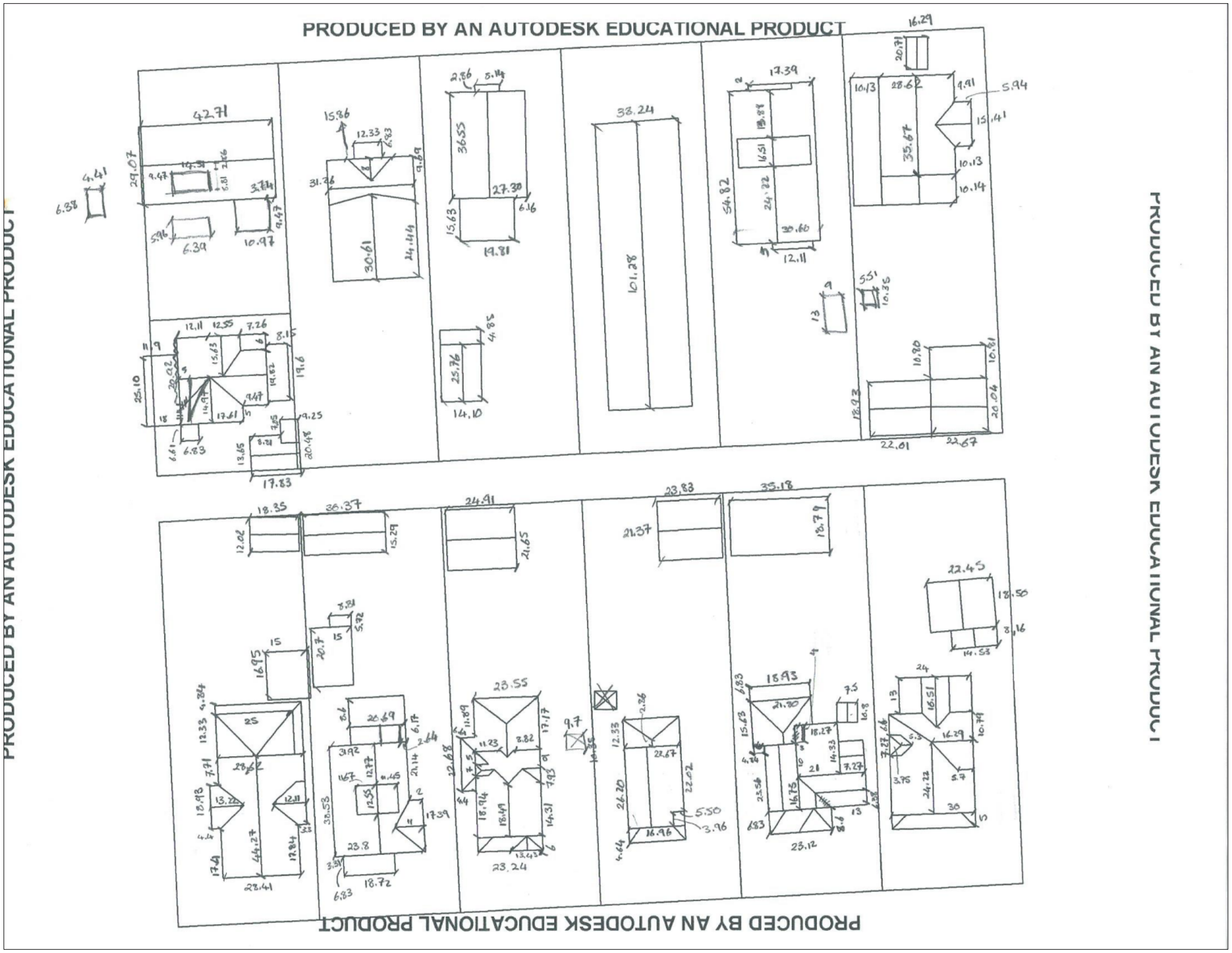

Figure 85. Example of sheets used for recording dimensions of roof lines (Source: Author).

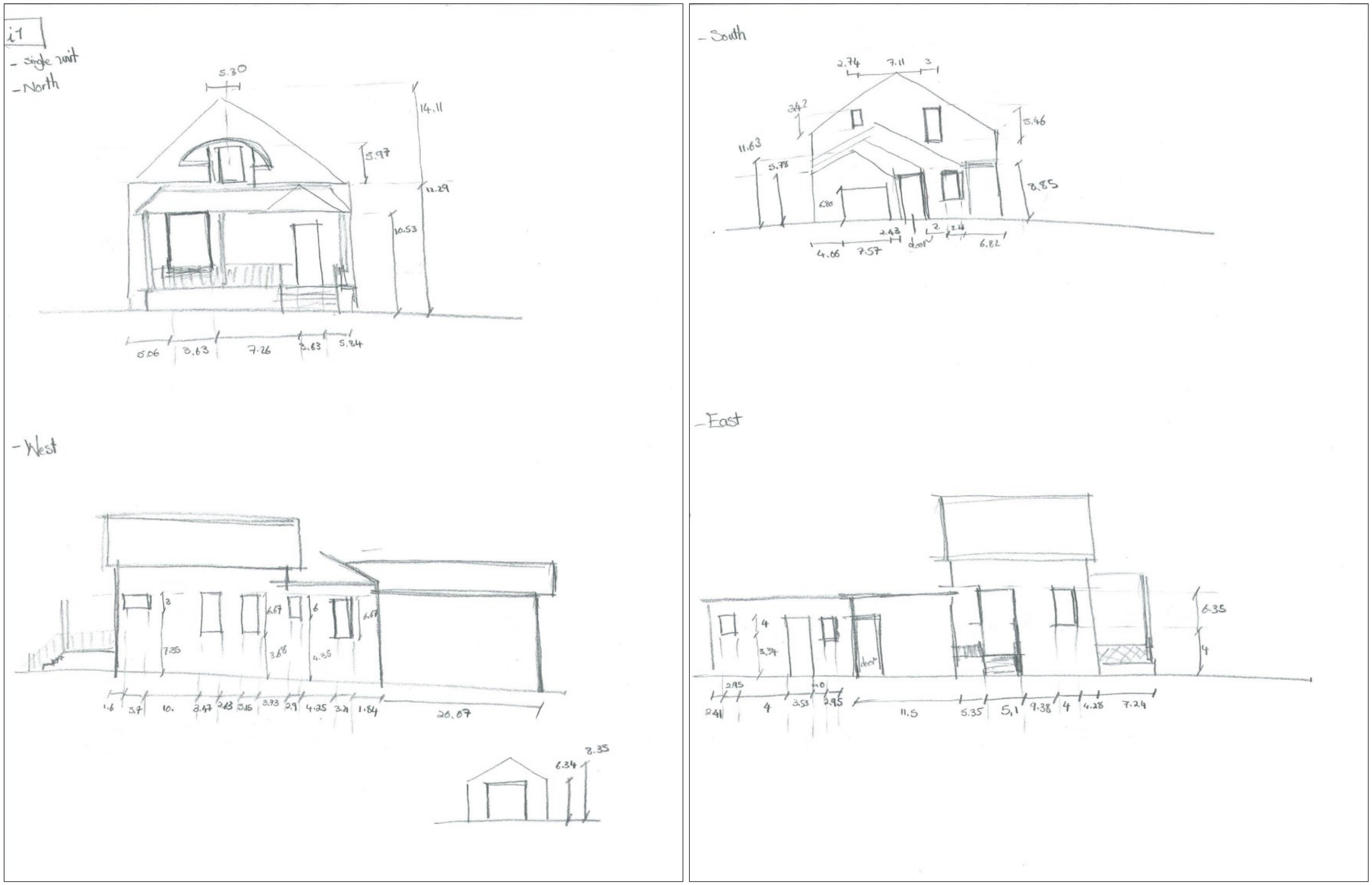

Figure 86. Example of sketches made of north, south, east and west building facades (Source: Author).

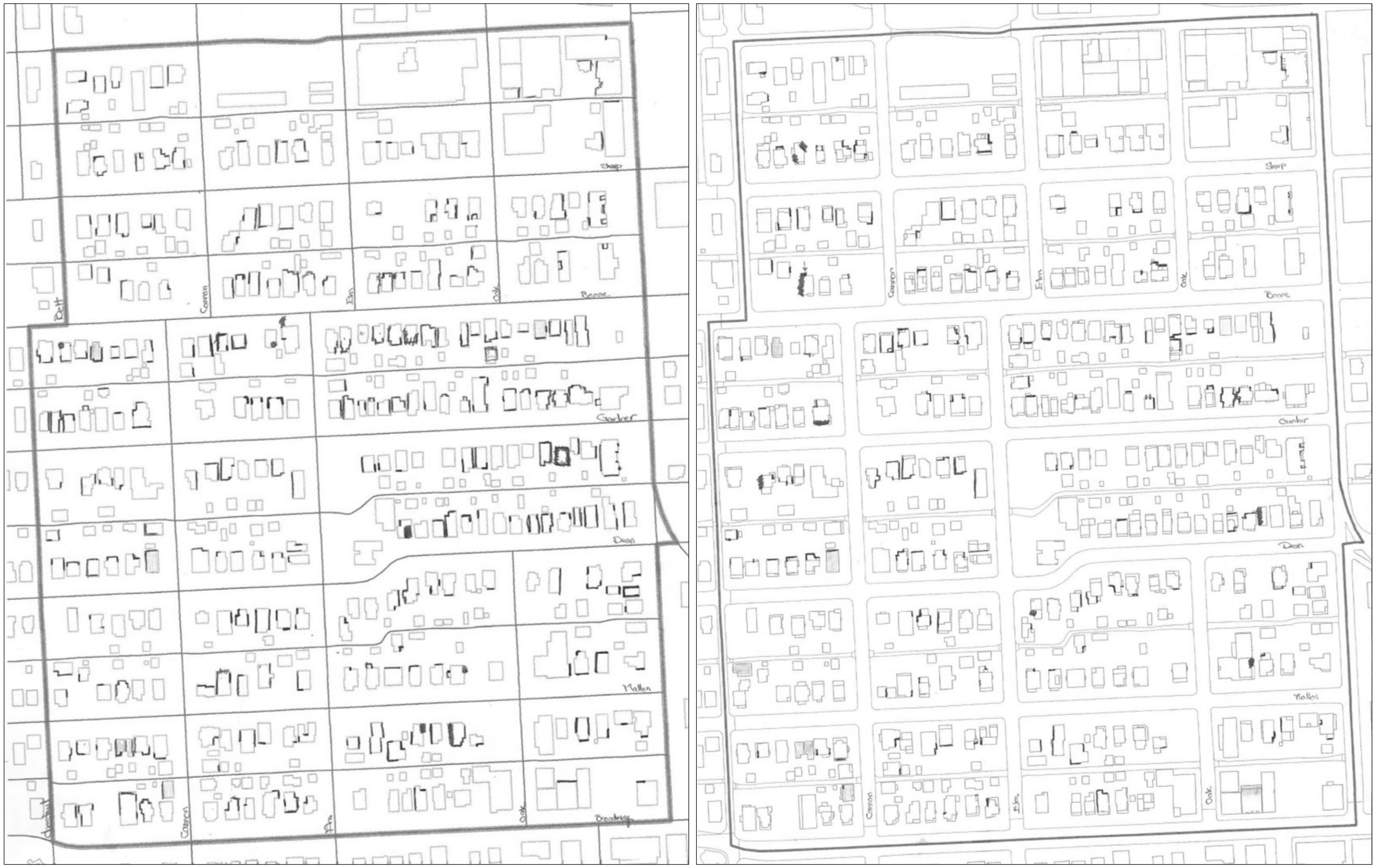

Figure 87. Examples of sheets for field observations of obscure building facades (Source: Author).

APPENDIX C: VARIATIONS IN SURVEILLABILITY

Number of possible and visible sightlines to buildings openings for different scenarios and sub-scenarios of the occupant, road and pedestrian surveillability categories were computed to help understand the role that each individual (buildings, street vegetation, yard vegetation and visual barriers) or combinations of variables might play in variations of surveillability in each category and distance. Tables in this section show information on (1) scenarios and sub-scenarios, (2) number of building openings with possible or visible sightlines, (3) number of building openings with no possible or visible sightlines, (4) sum total number of possible and visible sightlines, (5) difference between the number of possible and visible sightlines and (6) percent each individual or combinations of features changes the degree of natural surveillance.

C.1 Within 49 Feet Distance

For occupant surveillability. The number of visible sightlines compared to possible sightlines reduced by 91.24% (91.28%)[29] by introducing buildings as obstruction features in the first step of analysis of visibility. Taking into account one other feature (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 91.81% (91.84%), 91.24% (91.28%) and 91.86% (91.90%) for combinations of buildings and visual barriers, combinations of buildings and street vegetation and combinations of buildings and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of

[29] Percent each scenario reduced natural surveillance taking into account 2-dimentional length of sightlines are presented first, followed by percent each sub-scenario reduced natural surveillance taking into account 3-dimentional length of sightlines.

buildings and yard vegetation, followed by combinations of buildings and visual barriers and combinations of buildings and street vegetation.

Taking into consideration two other features (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 91.86% (91.90%), 91.81% (91.84%), 92.42% (92.45%) for combinations of buildings, street vegetation and yard vegetation, combinations of buildings, visual barriers and street vegetation and combinations of buildings, visual barriers and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, street vegetation and yard vegetation and combinations of buildings, visual barriers and street vegetation (See Table 107).

For road surveillability. The number of visible sightlines compared to possible sightlines reduced by 31.58% (33.27%) by introducing buildings as obstruction features in the first step of analysis of visibility. Taking into account one other feature (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 37.84% (39.38%), 31.58% (33.27%) and 34.92% (36.57%) for combinations of buildings and visual barriers, combinations of buildings and street vegetation and combinations of buildings and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and visual barriers, followed by combinations of buildings and yard vegetation and combinations of buildings and street vegetation.

Taking into consideration two other features (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 35.27% (36.92%), 37.84% (39.38%), 40.80% (42.30%) for combinations of buildings, street vegetation and yard vegetation, combinations of buildings, visual barriers and street vegetation and combinations of buildings, visual barriers and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, visual barriers and street vegetation and combinations of buildings, street vegetation and yard vegetation (See Table 108).

For pedestrian surveillability. The number of visible sightlines compared to possible sightlines reduced by 32.04% (32.31%) by introducing buildings as obstruction features in the first step of analysis of visibility. Taking into account one other feature (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 34.75% (34.99%), 32.20% (32.46%) and 36.31% (36.54%) for combinations of buildings and visual barriers, combinations of buildings and street vegetation and combinations of buildings and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and yard vegetation, followed by combinations of buildings and visual barriers and combinations of buildings and street vegetation.

Taking into consideration two other features (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 37.12% (37.35%), 34.90% (35.14%), 38.89% (39.10%) for combinations of buildings, street vegetation and yard vegetation, combinations of buildings, visual barriers and street vegetation and combinations of buildings, visual barriers and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, street vegetation and yard vegetation and combinations of buildings, visual barriers and street vegetation (See Table 109).

For occupant and pedestrian surveillability, taking into account one other feature along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and yard vegetation, followed by combinations of buildings and visual barriers and combinations of buildings and street vegetation. In addition, taking into consideration two other features along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, street vegetation and yard vegetation and combinations of buildings, visual barriers and street vegetation.

For road surveillability. Taking into account one other feature along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and visual barriers, followed by combinations of buildings and yard vegetation and combinations of buildings and street vegetation. In addition, taking into consideration two other features along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, visual barriers and street vegetation and combinations of buildings, street vegetation and yard vegetation.

Table 107

Variations in occupant surveillability within 49 feet of building openings (Source: Author).

Scenarios and sub-scenarios	# building openings with sightlines	# building openings with no sightlines	# possible and visible sightlines	Difference†	% reduction‡
Op_SightLine	3,179	0	95,405*	0	0.00
Op_LineOfSight_Bldg_Vis	2,099	1,080	8,358	87,047	91.24
Op_LineOfSight_Bldg_Vis_Len	2,095	1,084	8,324	87,081	91.28
Op_LineOfSight_Bldg_Bar_Vis	2,039	1,140	7,815	87,590	91.81
Op_LineOfSight_Bldg_Bar_Vis_Len	2,033	1,146	7,781	87,624	91.84
Op_LineOfSight_Bldg_Veg_St_Vis	2,099	1,080	8,358	87,047	91.24
Op_LineOfSight_Bldg_Veg_St_Vis_Len	2,095	1,084	8,324	87,081	91.28
Op_LineOfSight_Bldg_Veg_Ya_Vis	2,067	1,112	7,763	87,642	91.86
Op_LineOfSight_Bldg_Veg_Ya_Vis_Len	2,063	1,116	7,732	87,673	91.90
Op_LineOfSight_Bldg_Veg_Vis	2,067	1,112	7,763	87,642	91.86
Op_LineOfSight_Bldg_Veg_Vis_Len	2,063	1,116	7,732	87,673	91.90
Op_LineOfSight_Bldg_Veg_St_Bar_Vis	2,039	1,140	7,815	87,590	91.81
Op_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	2,033	1,146	7,781	87,624	91.84
Op_LineOfSight_Bldg_Veg_Ya_Bar_Vis	2,003	1,176	7,234	88,171	92.42
Op_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	1,997	1,182	7,203	88,202	92.45
Op_LineOfSight_Bldg_Veg_Bar_Vis	2,003	1,176	7,234	88,171	92.42
Op_LineOfSight_Bldg_Veg_Bar_Vis_Len	1,997	1,182	7,203	88,202	92.45

Notes:
* = number of possible sightlines. All other fields in that same column represent number of visible sightlines.
† Difference = number of possible sightlines – number of visible sightlines in each scenario and sub-scenario.
‡% reduction = (difference / number of possible sightlines) x 100

Table 108

Variations in road surveillability within 49 feet of building openings (Source: Author).

Scenarios and sub-scenarios	# building openings with sightlines	# building openings with no sightlines	# possible and visible sightlines	Difference†	% reduction‡
Rd_SightLine	666	2,513	2,603*	0	0.00
Rd_LineOfSight_Bldg_Vis	584	2,595	1,781	822	31.58
Rd_LineOfSight_Bldg_Vis_Len	576	2,603	1,737	866	33.27
Rd_LineOfSight_Bldg_Bar_Vis	530	2,649	1,618	985	37.84
Rd_LineOfSight_Bldg_Bar_Vis_Len	523	2,656	1,578	1,025	39.38
Rd_LineOfSight_Bldg_Veg_St_Vis	584	2,595	1,781	822	31.58
Rd_LineOfSight_Bldg_Veg_St_Vis_Len	576	2,603	1,737	866	33.27
Rd_LineOfSight_Bldg_Veg_Ya_Vis	565	2,614	1,694	909	34.92
Rd_LineOfSight_Bldg_Veg_Ya_Vis_Len	556	2,623	1,651	952	36.57
Rd_LineOfSight_Bldg_Veg_Vis	564	2,615	1,685	918	35.27
Rd_LineOfSight_Bldg_Veg_Vis_Len	555	2,624	1,642	961	36.92
Rd_LineOfSight_Bldg_Veg_St_Bar_Vis	530	2,649	1,618	985	37.84
Rd_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	523	2,656	1,578	1,025	39.38
Rd_LineOfSight_Bldg_Veg_Ya_Bar_Vis	514	2,665	1,541	1,062	40.80
Rd_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	506	2,673	1,502	1,101	42.30
Rd_LineOfSight_Bldg_Veg_Bar_Vis	513	2,666	1,532	1,071	41.14
Rd_LineOfSight_Bldg_Veg_Bar_Vis_Len	505	2,674	1,493	1,110	42.64

Notes:
* = number of possible sightlines. All other fields in that same column represent number of visible sightlines.
† Difference = number of possible sightlines – number of visible sightlines in each scenario and sub-scenario.
‡% reduction = (difference / number of possible sightlines) x 100

Table 109

Variations in pedestrian surveillability within 49 feet of building openings (Source: Author).

Scenarios and sub-scenarios	# building openings with sightlines	# building openings with no sightlines	# possible and visible sightlines	Difference†	% reduction‡
Sw_SightLine	1,531	1,648	21,458*	0	0.00
Sw_LineOfSight_Bldg_Vis	1,411	1,768	14,582	6,876	32.04
Sw_LineOfSight_Bldg_Vis_Len	1,409	1,770	14,525	6,933	32.31
Sw_LineOfSight_Bldg_Bar_Vis	1,345	1,834	14,002	7,456	34.75
Sw_LineOfSight_Bldg_Bar_Vis_Len	1,343	1,836	13,950	7,508	34.99
Sw_LineOfSight_Bldg_Veg_St_Vis	1,411	1,768	14,549	6,909	32.20
Sw_LineOfSight_Bldg_Veg_St_Vis_Len	1,409	1,770	14,492	6,966	32.46
Sw_LineOfSight_Bldg_Veg_Ya_Vis	1,381	1,798	13,667	7,791	36.31
Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len	1,379	1,800	13,617	7,841	36.54
Sw_LineOfSight_Bldg_Veg_Vis	1,381	1,798	13,492	7,966	37.12
Sw_LineOfSight_Bldg_Veg_Vis_Len	1,379	1,800	13,443	8,015	37.35
Sw_LineOfSight_Bldg_Veg_St_Bar_Vis	1,345	1,834	13,970	7,488	34.90
Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	1,343	1,836	13,918	7,540	35.14
Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis	1,316	1,863	13,112	8,346	38.89
Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	1,314	1,865	13,067	8,391	39.10
Sw_LineOfSight_Bldg_Veg_Bar_Vis	1,316	1,863	12,938	8,520	39.71
Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len	1,314	1,865	12,894	8,564	39.91

Notes:
* = number of possible sightlines. All other fields in that same column represent number of visible sightlines.
† Difference = number of possible sightlines – number of visible sightlines in each scenario and sub-scenario.
‡% reduction = (difference / number of possible sightlines) x 100

C.2 Within 95 Feet Distance

For occupant surveillability. The number of visible sightlines compared to possible sightlines reduced by 93.64% (93.66%) by introducing buildings as obstruction features in the first step of analysis of visibility. Taking into account one other feature (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 94.17% (94.19%), 93.64% (93.66%) and 94.22% (94.24%) for combinations of buildings and visual barriers, combinations of buildings and street vegetation and combinations of buildings and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and yard vegetation, followed by combinations of buildings and visual barriers and combinations of buildings and street vegetation.

Taking into consideration two other features (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 94.25% (94.27%), 94.17% (94.19%), 94.72% (94.74%) for combinations of buildings, street vegetation and yard vegetation, combinations of buildings, visual barriers and street vegetation and combinations of buildings, visual barriers and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, street vegetation and yard vegetation and combinations of buildings, visual barriers and street vegetation (See Table 110).

For road surveillability. The number of visible sightlines compared to possible sightlines reduced by 55.47% (55.60%) by introducing buildings as obstruction features in the first step of analysis of visibility. Taking into account one other feature (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 62.13% (62.24%), 55.54% (55.67%) and 59.30% (59.40%) for combinations of buildings and visual barriers, combinations of buildings and street vegetation and combinations of buildings and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and visual barriers, followed by combinations of buildings and yard vegetation and combinations of buildings and street vegetation.

Taking into consideration two other features (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 59.72% (59.83%), 62.19% (62.30%), 65.25% (65.34%) for combinations of buildings, street vegetation and yard vegetation, combinations of buildings, visual barriers and street vegetation and combinations of buildings, visual barriers and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, visual barriers and street vegetation and combinations of buildings, street vegetation and yard vegetation (See Table 111).

For pedestrian surveillability. The number of visible sightlines compared to possible sightlines reduced by 57.04% (57.08%) by introducing buildings as obstruction features in the first step of analysis of visibility. Taking into account one other feature (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 60.90% (60.94%), 57.14% (57.19%) and 60.81% (60.85%) for combinations of buildings and visual barriers, combinations of buildings and street vegetation and combinations of buildings and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and visual barriers, followed by combinations of buildings and yard vegetation and combinations of buildings and street vegetation.

Taking into consideration two other features (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 61.36% (61.40%), 61.00% (61.04%), 64.31% (64.34%) for combinations of buildings, street vegetation and yard vegetation, combinations of buildings, visual barriers and street vegetation and combinations of buildings, visual barriers and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, street vegetation and yard vegetation and combinations of buildings, visual barriers and street vegetation (See Table 112).

For occupant surveillability, taking into account one other feature along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and yard vegetation, followed by combinations of buildings and visual barriers and combinations of buildings and street vegetation. In addition, taking into consideration two other features along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, street vegetation and yard vegetation and combinations of buildings, visual barriers and street vegetation.

For road surveillability. Taking into account one other feature along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and visual barriers, followed by combinations of buildings and yard vegetation and combinations of buildings and street vegetation. In addition, taking into consideration two other features along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, visual barriers and street vegetation and combinations of buildings, street vegetation and yard vegetation.

For pedestrian surveillability, taking into account one other feature along with buildings, the maximum reduction in the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and visual barriers, followed by combinations of buildings and yard vegetation and combinations of buildings and street vegetation. In addition, taking into consideration two other features along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, street vegetation and yard vegetation and combinations of buildings, visual barriers and street vegetation.

Table 110

Variations in occupant surveillability within 95 feet of building openings (Source: Author).

Scenarios and sub-scenarios	# building openings with sightlines	# building openings with no sightlines	# possible and visible sightlines	Difference†	% reduction‡
Op_SightLine	3,179	0	208,469*	0	0.00
Op_LineOfSight_Bldg_Vis	2,554	625	13,268	195,201	93.64
Op_LineOfSight_Bldg_Vis_Len	2,552	627	13,224	195,245	93.66
Op_LineOfSight_Bldg_Bar_Vis	2,475	704	12,164	196,305	94.17
Op_LineOfSight_Bldg_Bar_Vis_Len	2,471	708	12,120	196,349	94.19
Op_LineOfSight_Bldg_Veg_St_Vis	2,554	625	13,268	195,201	93.64
Op_LineOfSight_Bldg_Veg_St_Vis_Len	2,552	627	13,224	195,245	93.66
Op_LineOfSight_Bldg_Veg_Ya_Vis	2,521	658	12,049	196,420	94.22
Op_LineOfSight_Bldg_Veg_Ya_Vis_Len	2,518	661	12,009	196,460	94.24
Op_LineOfSight_Bldg_Veg_Vis	2,521	658	11,981	196,488	94.25
Op_LineOfSight_Bldg_Veg_Vis_Len	2,518	661	11,943	196,526	94.27
Op_LineOfSight_Bldg_Veg_St_Bar_Vis	2,475	704	12,164	196,305	94.17
Op_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	2,471	708	12,120	196,349	94.19
Op_LineOfSight_Bldg_Veg_Ya_Bar_Vis	2,439	740	11,007	197,462	94.72
Op_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	2,435	744	10,967	197,502	94.74
Op_LineOfSight_Bldg_Veg_Bar_Vis	2,439	740	10,939	197,530	94.75
Op_LineOfSight_Bldg_Veg_Bar_Vis_Len	2,435	744	10,901	197,568	94.77

Notes:
* = number of possible sightlines. All other fields in that same column represent number of visible sightlines.
† Difference = number of possible sightlines – number of visible sightlines in each scenario and sub-scenario.
‡% reduction = (difference / number of possible sightlines) x 100

Table 111

Variations in road surveillability within 95 feet of building openings (Source: Author).

Scenarios and sub-scenarios	# building openings with sightlines	# building openings with no sightlines	# possible and visible sightlines	Difference†	% reduction‡
Rd_SightLine	3,171	8	42,012*	0	0.00
Rd_LineOfSight_Bldg_Vis	2,956	223	18,706	23,306	55.47
Rd_LineOfSight_Bldg_Vis_Len	2,954	225	18,654	23,358	55.60
Rd_LineOfSight_Bldg_Bar_Vis	2,548	631	15,910	26,102	62.13
Rd_LineOfSight_Bldg_Bar_Vis_Len	2,546	633	15,865	26,147	62.24
Rd_LineOfSight_Bldg_Veg_St_Vis	2,956	223	18,678	23,334	55.54
Rd_LineOfSight_Bldg_Veg_St_Vis_Len	2,954	225	18,626	23,386	55.67
Rd_LineOfSight_Bldg_Veg_Ya_Vis	2,893	286	17,100	24,912	59.30
Rd_LineOfSight_Bldg_Veg_Ya_Vis_Len	2,891	288	17,056	24,956	59.40
Rd_LineOfSight_Bldg_Veg_Vis	2,892	287	16,921	25,091	59.72
Rd_LineOfSight_Bldg_Veg_Vis_Len	2,890	289	16,878	25,134	59.83
Rd_LineOfSight_Bldg_Veg_St_Bar_Vis	2,548	631	15,884	26,128	62.19
Rd_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	2,546	633	15,839	26,173	62.30
Rd_LineOfSight_Bldg_Veg_Ya_Bar_Vis	2,482	697	14,599	27,413	65.25
Rd_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	2,480	699	14,562	27,450	65.34
Rd_LineOfSight_Bldg_Veg_Bar_Vis	2,481	698	14,429	27,583	65.66
Rd_LineOfSight_Bldg_Veg_Bar_Vis_Len	2,479	700	14,393	27,619	65.74

Notes:
* = number of possible sightlines. All other fields in that same column represent number of visible sightlines.
† Difference = number of possible sightlines – number of visible sightlines in each scenario and sub-scenario.
‡% reduction = (difference / number of possible sightlines) x 100

Table 112

Variations in pedestrian surveillability within 95 feet of building openings (Source: Author).

Scenarios and sub-scenarios	# building openings with sightlines	# building openings with no sightlines	# possible and visible sightlines	Difference†	% reduction‡
Sw_SightLine	3,179	0	192,411*	0	0.00
Sw_LineOfSight_Bldg_Vis	3,054	125	82,659	109,752	57.04
Sw_LineOfSight_Bldg_Vis_Len	3,054	125	82,577	109,834	57.08
Sw_LineOfSight_Bldg_Bar_Vis	2,831	348	75,227	117,184	60.90
Sw_LineOfSight_Bldg_Bar_Vis_Len	2,831	348	75,151	117,260	60.94
Sw_LineOfSight_Bldg_Veg_St_Vis	3,054	125	82,460	109,951	57.14
Sw_LineOfSight_Bldg_Veg_St_Vis_Len	3,054	125	82,378	110,033	57.19
Sw_LineOfSight_Bldg_Veg_Ya_Vis	3,018	161	75,413	116,998	60.81
Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len	3,018	161	75,332	117,079	60.85
Sw_LineOfSight_Bldg_Veg_Vis	3,018	161	74,349	118,062	61.36
Sw_LineOfSight_Bldg_Veg_Vis_Len	3,018	161	74,270	118,141	61.40
Sw_LineOfSight_Bldg_Veg_St_Bar_Vis	2,830	349	75,036	117,375	61.00
Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	2,830	349	74,960	117,451	61.04
Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis	2,777	402	68,680	123,731	64.31
Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	2,777	402	68,605	123,806	64.34
Sw_LineOfSight_Bldg_Veg_Bar_Vis	2,777	402	67,649	124,762	64.84
Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len	2,777	402	67,576	124,835	64.88

Notes:
* = number of possible sightlines. All other fields in that same column represent number of visible sightlines.
† Difference = number of possible sightlines – number of visible sightlines in each scenario and sub-scenario.
‡% reduction = (difference / number of possible sightlines) x 100

C.3 Within 141 Feet Distance

For occupant surveillability. The number of visible sightlines compared to possible sightlines reduced by 90.28% (90.31%) by introducing buildings as obstruction features in the first step of analysis of visibility. Taking into account one other feature (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 91.04% (91.06%), 90.34% (90.37%) and 91.78% (91.79%) for combinations of buildings and visual barriers, combinations of buildings and street vegetation and combinations of buildings and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and yard vegetation, followed by combinations of buildings and visual barriers and combinations of buildings and street vegetation.

Taking into consideration two other features (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 91.97% (91.99%), 91.09% (91.12%), 92.45% (92.46%) for combinations of buildings, street vegetation and yard vegetation, combinations of buildings, visual barriers and street vegetation and combinations of buildings, visual barriers and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, street vegetation and yard vegetation and combinations of buildings, visual barriers and street vegetation (See Table 113).

For road surveillability. The number of visible sightlines compared to possible sightlines reduced by 71.18% (71.19%) by introducing buildings as obstruction features in the first step of analysis of visibility. Taking into account one other feature (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 75.86% (75.87%), 71.22% (71.24%) and 73.96% (73.97%) for combinations of buildings and visual barriers, combinations of buildings and street vegetation and combinations of buildings and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and visual barriers, followed by combinations of buildings and yard vegetation and combinations of buildings and street vegetation.

Taking into consideration two other features (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 74.29% (74.30%), 75.90% (75.91%), 78.14% (78.15%) for combinations of buildings, street vegetation and yard vegetation, combinations of buildings, visual barriers and street vegetation and combinations of buildings, visual barriers and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, visual barriers and street vegetation and combinations of buildings, street vegetation and yard vegetation (See Table 114).

For pedestrian surveillability. The number of visible sightlines compared to possible sightlines reduced by 69.96% (69.97%) by introducing buildings as obstruction features in the first step of analysis of visibility. Taking into account one other feature (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 72.92% (72.93%), 70.04% (70.05%) and 73.02% (73.03%) for combinations of buildings and visual barriers, combinations of buildings and street vegetation and combinations of buildings and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and yard vegetation, followed by combinations of buildings and visual barriers and combinations of buildings and street vegetation.

Taking into consideration two other features (i.e. visual barriers, yard vegetation and street vegetation) along with buildings, the number of visible sightlines compared to possible sightlines decreased by 73.48% (73.49%), 73.00% (73.01%), 75.65% (75.65%) for combinations of buildings, street vegetation and yard vegetation, combinations of buildings, visual barriers and street vegetation and combinations of buildings, visual barriers and yard vegetation respectively. Thus, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, street vegetation and yard vegetation and combinations of buildings, visual barriers and street vegetation (See Table 115).

For occupant and pedestrian surveillability, taking into account one other feature along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and yard vegetation, followed by combinations of buildings and visual barriers and combinations of buildings and street vegetation. In addition, taking into consideration two other features along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, street vegetation and yard vegetation and combinations of buildings, visual barriers and street vegetation.

For road surveillability. Taking into account one other feature along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings and visual barriers, followed by combinations of buildings and yard vegetation and combinations of buildings and street vegetation. In addition, taking into consideration two other features along with buildings, the maximum reduction in the number of visible sightlines compared to possible sightlines occurred for combinations of buildings, visual barriers and yard vegetation followed by combinations of buildings, visual barriers and street vegetation and combinations of buildings, street vegetation and yard vegetation.

Table 113

Variations in occupant surveillability within 141 feet of building openings (Source: Author).

Scenarios and sub-scenarios	# building openings with sightlines	# building openings with no sightlines	# possible and visible sightlines	Difference†	% reduction‡
Op_SightLine	3,179	0	374,234*	0	0.00
Op_LineOfSight_Bldg_Vis	3,028	151	36,361	337,873	90.28
Op_LineOfSight_Bldg_Vis_Len	3,028	151	36,252	337,982	90.31
Op_LineOfSight_Bldg_Bar_Vis	2,970	209	33,537	340,697	91.04
Op_LineOfSight_Bldg_Bar_Vis_Len	2,969	210	33,441	340,793	91.06
Op_LineOfSight_Bldg_Veg_St_Vis	3,028	151	36,151	338,083	90.34
Op_LineOfSight_Bldg_Veg_St_Vis_Len	3,028	151	36,042	338,192	90.37
Op_LineOfSight_Bldg_Veg_Ya_Vis	2,992	187	30,777	343,457	91.78
Op_LineOfSight_Bldg_Veg_Ya_Vis_Len	2,992	187	30,706	343,528	91.79
Op_LineOfSight_Bldg_Veg_Vis	2,992	187	30,046	344,188	91.97
Op_LineOfSight_Bldg_Veg_Vis_Len	2,992	187	29,979	344,255	91.99
Op_LineOfSight_Bldg_Veg_St_Bar_Vis	2,970	209	33,327	340,907	91.09
Op_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	2,969	210	33,231	341,003	91.12
Op_LineOfSight_Bldg_Veg_Ya_Bar_Vis	2,928	251	28,272	345,962	92.45
Op_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	2,927	252	28,212	346,022	92.46
Op_LineOfSight_Bldg_Veg_Bar_Vis	2,928	251	27,544	346,690	92.64
Op_LineOfSight_Bldg_Veg_Bar_Vis_Len	2,927	252	27,488	346,746	92.65

Notes:
* = number of possible sightlines. All other fields in that same column represent number of visible sightlines.
† Difference = number of possible sightlines – number of visible sightlines in each scenario and sub-scenario.
‡% reduction = (difference / number of possible sightlines) x 100

Table 114

Variations in road surveillability within 141 feet of building openings (Source: Author).

Scenarios and sub-scenarios	# building openings with sightlines	# building openings with no sightlines	# possible and visible sightlines	Difference†	% reduction‡
Rd_SightLine	3,179	0	114,882*	0	0.00
Rd_LineOfSight_Bldg_Vis	3,102	77	33,113	81,769	71.18
Rd_LineOfSight_Bldg_Vis_Len	3,102	77	33,094	81,788	71.19
Rd_LineOfSight_Bldg_Bar_Vis	2,743	436	27,734	87,148	75.86
Rd_LineOfSight_Bldg_Bar_Vis_Len	2,743	436	27,716	87,166	75.87
Rd_LineOfSight_Bldg_Veg_St_Vis	3,102	77	33,063	81,819	71.22
Rd_LineOfSight_Bldg_Veg_St_Vis_Len	3,102	77	33,044	81,838	71.24
Rd_LineOfSight_Bldg_Veg_Ya_Vis	3,057	122	29,916	84,966	73.96
Rd_LineOfSight_Bldg_Veg_Ya_Vis_Len	3,057	122	29,903	84,979	73.97
Rd_LineOfSight_Bldg_Veg_Vis	3,057	122	29,538	85,344	74.29
Rd_LineOfSight_Bldg_Veg_Vis_Len	3,057	122	29,525	85,357	74.30
Rd_LineOfSight_Bldg_Veg_St_Bar_Vis	2,743	436	27,689	87,193	75.90
Rd_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	2,743	436	27,671	87,211	75.91
Rd_LineOfSight_Bldg_Veg_Ya_Bar_Vis	2,680	499	25,115	89,767	78.14
Rd_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	2,680	499	25,103	89,779	78.15
Rd_LineOfSight_Bldg_Veg_Bar_Vis	2,680	499	24,759	90,123	78.45
Rd_LineOfSight_Bldg_Veg_Bar_Vis_Len	2,680	499	24,747	90,135	78.46

Notes:
* = number of possible sightlines. All other fields in that same column represent number of visible sightlines.
† Difference = number of possible sightlines – number of visible sightlines in each scenario and sub-scenario.
‡% reduction = (difference / number of possible sightlines) x 100

Table 115

Variations in pedestrian surveillability within 141 feet of building openings (Source: Author).

Scenarios and sub-scenarios	# building openings with sightlines	# building openings with no sightlines	# possible and visible sightlines	Difference†	% reduction‡
Sw_SightLine	3,179	0	496,892*	0	0.00
Sw_LineOfSight_Bldg_Vis	3,122	57	149,254	347,638	69.96
Sw_LineOfSight_Bldg_Vis_Len	3,122	57	149,212	347,680	69.97
Sw_LineOfSight_Bldg_Bar_Vis	2,916	263	134,539	362,353	72.92
Sw_LineOfSight_Bldg_Bar_Vis_Len	2,916	263	134,498	362,394	72.93
Sw_LineOfSight_Bldg_Veg_St_Vis	3,122	57	148,862	348,030	70.04
Sw_LineOfSight_Bldg_Veg_St_Vis_Len	3,122	57	148,820	348,072	70.05
Sw_LineOfSight_Bldg_Veg_Ya_Vis	3,093	86	134,061	362,831	73.02
Sw_LineOfSight_Bldg_Veg_Ya_Vis_Len	3,093	86	134,023	362,869	73.03
Sw_LineOfSight_Bldg_Veg_Vis	3,093	86	131,767	365,125	73.48
Sw_LineOfSight_Bldg_Veg_Vis_Len	3,093	86	131,730	365,162	73.49
Sw_LineOfSight_Bldg_Veg_St_Bar_Vis	2,916	263	134,163	362,729	73.00
Sw_LineOfSight_Bldg_Veg_St_Bar_Vis_Len	2,916	263	134,122	362,770	73.01
Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis	2,867	312	121,009	375,883	75.65
Sw_LineOfSight_Bldg_Veg_Ya_Bar_Vis_Len	2,867	312	120,972	375,920	75.65
Sw_LineOfSight_Bldg_Veg_Bar_Vis	2,867	312	118,791	378,101	76.09
Sw_LineOfSight_Bldg_Veg_Bar_Vis_Len	2,867	312	118,755	378,137	76.10

Notes:
* = number of possible sightlines. All other fields in that same column represent number of visible sightlines.
† Difference = number of possible sightlines – number of visible sightlines in each scenario and sub-scenario.
‡% reduction = (difference / number of possible sightlines) x 100

APPENDIX D: CHI-SQUARE STATISTICS

D.1 Chi-square Statistics for Building Openings

Building use. The results of chi-square statistics indicated a statistically significant difference between building openings to single or multi-family dwellings and burglary commissions ($\chi^2 = 5.94$, df = 1, $p = 0.02$). The odds of burglary commission through building openings to single family dwellings was 0.55 times the odds of burglary commission through building openings to multi-family dwellings (OR = 0.55, 95% CI = 0.33-0.90). Further, the risk of burglary commissions was reduced by 46% in building openings to single family dwellings compared to building openings to multi-family dwellings (RR = 0.56, 95% CI = 0.34-0.90) (See *Figure 88*).

			Offence_141		
			Burglarized	Not Burglarized	Total
Bldg_Use_2Types_2Plus Units	1 Unit	Count	35	2121	2156
		Expected Count	44.1	2111.9	2156.0
	2 Plus Units	Count	30	993	1023
		Expected Count	20.9	1002.1	1023.0
Total		Count	65	3114	3179
		Expected Count	65.0	3114.0	3179.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	5.937[a]	1	.015		
Continuity Correction[b]	5.301	1	.021		
Likelihood Ratio	5.609	1	.018		
Fisher's Exact Test				.022	.012
N of Valid Cases	3179				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 20.92.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Bldg_Use_2Types_2Plus Units (1 Unit / 2 Plus Units)	.546	.333	.895
For cohort Offence_141 = Burglarized	.554	.342	.896
For cohort Offence_141 = Not Burglarized	1.013	1.001	1.026
N of Valid Cases	3179		

Figure 88. The relationship between building use and burglary commissions (Source: Author).

Corner or middle lot. The results of chi-square statistics indicated an insignificant relationship between building openings to corner or middle lot dwellings and burglary commissions ($\chi^2 = 3.48$, df = 1, $p > 0.05$) (See *Figure 89*).

			Offence_141		
			Burglarized	Not Burglarized	Total
CornerMiddle_Lot_Corner	Middle Lot	Count	42	2329	2371
		Expected Count	48.5	2322.5	2371.0
	Corner Lot	Count	23	785	808
		Expected Count	16.5	791.5	808.0
Total		Count	65	3114	3179
		Expected Count	65.0	3114.0	3179.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.478[a]	1	.062		
Continuity Correction[b]	2.962	1	.085		
Likelihood Ratio	3.240	1	.072		
Fisher's Exact Test				.083	.046
N of Valid Cases	3179				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 16.52.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for CornerMiddle_Lot_Corner (Middle Lot / Corner Lot)	.615	.368	1.030
For cohort Offence_141 = Burglarized	.622	.377	1.028
For cohort Offence_141 = Not Burglarized	1.011	.998	1.024
N of Valid Cases	3179		

Figure 89. The relationship between belonging to a corner or middle lot and burglary commissions (Source: Author).

Vacant lot. The results of chi-square statistics indicated a statistically significant difference between adjacency to a vacant lot and burglary commissions ($\chi^2 = 4.73$, df = 1, Fisher's exact $p = 0.04$). The odds of burglary commission through building openings away from vacant lots was 0.42 times the odds of burglary commission through building openings adjacent to vacant lots (OR = 0.42, 95% CI = 0.19-0.94). Further, the risk of burglary commissions was reduced by 57% for building openings away from vacant lots compared to building openings adjacent to vacant lots (RR = 0.43, 95% CI = 0.20-0.93) (See *Figure 90*).

			Offence_141		
			Burglarized	Not Burglarized	Total
Adjacent_Vacant_Yes	No	Count	58	2963	3021
		Expected Count	61.8	2959.2	3021.0
	Yes	Count	7	151	158
		Expected Count	3.2	154.8	158.0
Total		Count	65	3114	3179
		Expected Count	65.0	3114.0	3179.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	4.725[a]	1	.030	.040	.040
Continuity Correction[b]	3.554	1	.059		
Likelihood Ratio	3.619	1	.057	.076	.040
Fisher's Exact Test				.040	.040
N of Valid Cases	3179				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 3.23.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Adjacent_Vacant_Yes (No / Yes)	.422	.190	.941
For cohort Offence_141 = Burglarized	.433	.201	.934
For cohort Offence_141 = Not Burglarized	1.026	.992	1.062
N of Valid Cases	3179		

Figure 90. The relationship between adjacency to vacant lots and burglary commissions (Source: Author).

Maintenance. The results of the chi-square statistics indicated an insignificant relationship between maintenance and burglary commissions ($\chi^2 = 0.00$, df = 1, $p > 0.05$) (See *Figure 91*).

			Offence_141		
			Burglarized	Not Burglarized	Total
Maintenance_Yes	No	Count	33	1588	1621
		Expected Count	33.1	1587.9	1621.0
	Yes	Count	32	1526	1558
		Expected Count	31.9	1526.1	1558.0
Total		Count	65	3114	3179
		Expected Count	65.0	3114.0	3179.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.001[a]	1	.971		
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.001	1	.971		
Fisher's Exact Test				1.000	.535
N of Valid Cases	3179				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 31.86.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Maintenance_Yes (No / Yes)	.991	.606	1.620
For cohort Offence_141 = Burglarized	.991	.613	1.604
For cohort Offence_141 = Not Burglarized	1.000	.990	1.010
N of Valid Cases	3179		

Figure 91. The relationship between maintenance and burglary commissions (Source: Author).

No-trespassing symbols. The results of chi-square statistics indicated an insignificant relationship between availability of no-trespassing signs and burglary commissions ($\chi^2 = 1.30$, df $= 1$, $p > 0.05$) (See *Figure 92*).

			Offence_141		
			Burglarized	Not Burglarized	Total
Trespass_Sign_Yes	No	Count	53	2692	2745
		Expected Count	56.1	2688.9	2745.0
	Yes	Count	12	422	434
		Expected Count	8.9	425.1	434.0
Total		Count	65	3114	3179
		Expected Count	65.0	3114.0	3179.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.302[a]	1	.254		
Continuity Correction[b]	.919	1	.338		
Likelihood Ratio	1.195	1	.274		
Fisher's Exact Test				.271	.167
N of Valid Cases	3179				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 8.87.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Trespass_Sign_Yes (No / Yes)	.692	.367	1.306
For cohort Offence_141 = Burglarized	.698	.376	1.296
For cohort Offence_141 = Not Burglarized	1.009	.992	1.026
N of Valid Cases	3179		

Figure 92. The relationship between availability of no-trespassing signs and burglary commissions (Source: Author).

Diversity. The results of chi-square statistics demonstrated an insignificant relationship between presence or absence of non-residential facilities within 49 ($\chi^2 = 0.09$, df = 1, Fisher's exact $p > 0.05$), 95 ($\chi^2 = 0.51$, df = 1, $p > 0.05$) and 141 ($\chi^2 = 1.73$, df = 1, $p > 0.05$) feet of building openings and burglary commissions (See *Figure 93*, *Figure 94* and *Figure 95*).

			Offence_141		
			Burglarized	Not Burglarized	Total
Facilities_49_Yes	No	Count	63	3036	3099
		Expected Count	63.4	3035.6	3099.0
	Yes	Count	2	78	80
		Expected Count	1.6	78.4	80.0
Total		Count	65	3114	3179
		Expected Count	65.0	3114.0	3179.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.085[a]	1	.771	1.000	.491
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.080	1	.778	1.000	.491
Fisher's Exact Test				.679	.491
N of Valid Cases	3179				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 1.64.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Facilities_49_Yes (No / Yes)	.809	.195	3.367
For cohort Offence_141 = Burglarized	.813	.203	3.265
For cohort Offence_141 = Not Burglarized	1.005	.970	1.041
N of Valid Cases	3179		

Figure 93. The relationship between diversity and burglary commissions within 49 feet of building openings (Source: Author).

			Offence_141		
			Burglarized	Not Burglarized	Total
Facilities_95_Yes	No	Count	60	2790	2850
		Expected Count	58.3	2791.7	2850.0
	Yes	Count	5	324	329
		Expected Count	6.7	322.3	329.0
Total		Count	65	3114	3179
		Expected Count	65.0	3114.0	3179.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.505[a]	1	.477		
Continuity Correction[b]	.255	1	.614		
Likelihood Ratio	.548	1	.459		
Fisher's Exact Test				.679	.321
N of Valid Cases	3179				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 6.73.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Facilities_95_Yes (No / Yes)	1.394	.556	3.495
For cohort Offence_141 = Burglarized	1.385	.560	3.425
For cohort Offence_141 = Not Burglarized	.994	.980	1.009
N of Valid Cases	3179		

Figure 94. The relationship between diversity and burglary commissions within 95 feet of building openings (Source: Author).

			Offence_141		
			Burglarized	Not Burglarized	Total
Facilities_141_Yes	No	Count	43	2287	2330
		Expected Count	47.6	2282.4	2330.0
	Yes	Count	22	827	849
		Expected Count	17.4	831.6	849.0
Total		Count	65	3114	3179
		Expected Count	65.0	3114.0	3179.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.728[a]	1	.189		
Continuity Correction[b]	1.376	1	.241		
Likelihood Ratio	1.646	1	.200		
Fisher's Exact Test				.202	.122
N of Valid Cases	3179				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 17.36.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Facilities_141_Yes (No / Yes)	.707	.420	1.189
For cohort Offence_141 = Burglarized	.712	.429	1.183
For cohort Offence_141 = Not Burglarized	1.008	.995	1.020
N of Valid Cases	3179		

Figure 95. The relationship between diversity and burglary commissions within 141 feet of building openings (Source: Author).

Territoriality. The results of chi-square statistics indicated a statistically significant difference between fenced and unfenced building openings and burglary commissions (χ^2 = 16.34, df = 1, $p < 0.001$). The odds of burglary commission through unfenced building openings was 3 times greater than burglary commission through fenced building openings (OR = 3.00, 95% CI = 1.72-5.23). Further, the risk of burglary commission through unfenced building openings was 3 times more likely than burglary commission through fenced building openings (RR = 2.93, 95% CI = 1.70-5.23) (See *Figure 96*).

			Offence_141		
			Burglarized	Not Burglarized	Total
Territory_Fencing	No Fencing	Count	48	1511	1559
		Expected Count	31.9	1527.1	1559.0
	Fencing	Count	17	1603	1620
		Expected Count	33.1	1586.9	1620.0
Total		Count	65	3114	3179
		Expected Count	65.0	3114.0	3179.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	16.338[a]	1	.000		
Continuity Correction[b]	15.341	1	.000		
Likelihood Ratio	16.951	1	.000		
Fisher's Exact Test				.000	.000
N of Valid Cases	3179				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 31.88.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Territory_Fencing (No Fencing / Fencing)	2.995	1.715	5.232
For cohort Offence_141 = Burglarized	2.934	1.695	5.079
For cohort Offence_141 = Not Burglarized	.979	.970	.990
N of Valid Cases	3179		

Figure 96. The relationship between territoriality and burglary commissions (Source: Author).

Facing of building openings. The results of chi-square statistics indicated a insignificant relationship between facing of building openings and burglary commissions ($\chi^2 = 9.15$, df = 3, Fisher's exact $p = 0.03$) (See *Figure 97*).

			Offence_141		
			Burglarized	Not Burglarized	Total
Opening_Face_4Types	Alley	Count	17	646	663
		Expected Count	13.6	649.4	663.0
	Building	Count	23	1585	1608
		Expected Count	32.9	1575.1	1608.0
	Neighborhood Collector	Count	6	120	126
		Expected Count	2.6	123.4	126.0
	Regional	Count	19	763	782
		Expected Count	16.0	766.0	782.0
Total		Count	65	3114	3179
		Expected Count	65.0	3114.0	3179.0

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)
Pearson Chi-Square	9.147[a]	3	.027	.028
Likelihood Ratio	8.149	3	.043	.051
Fisher's Exact Test	9.056			.024
N of Valid Cases	3179			

a. 1 cells (12.5%) have expected count less than 5. The minimum expected count is 2.58.

Figure 97. The relationship between facing of building openings and burglary commissions (Source: Author).

D.2 Chi-square Statistics for Dwellings

Building use. The results of chi-square statistics indicated an insignificant relationship between building use and burglary occurrence ($\chi^2 = 3.17$, df = 1, $p > 0.05$) (See *Figure 98*).

			FIRST_OFFENCE_14		
			Burglarized	Not Burglarized	Total
Bldg_Use_Coded	1 Unit	Count	38	119	157
		Expected Count	43.5	113.5	157.0
		% of Total	17.0%	53.1%	70.1%
	2 Plus Units	Count	24	43	67
		Expected Count	18.5	48.5	67.0
		% of Total	10.7%	19.2%	29.9%
Total		Count	62	162	224
		Expected Count	62.0	162.0	224.0
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.166[a]	1	.075		
Continuity Correction[b]	2.612	1	.106		
Likelihood Ratio	3.079	1	.079		
Fisher's Exact Test				.102	.054
N of Valid Cases	224				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 18.54.

b. Computed only for a 2x2 table

Risk Estimate

		95% Confidence Interval	
	Value	Lower	Upper
Odds Ratio for Bldg_Use_Coded (1 Unit / 2 Plus Units)	.572	.308	1.062
For cohort FIRST_OFFENCE_14 = Burglarized	.676	.442	1.032
For cohort FIRST_OFFENCE_14 = Not Burglarized	1.181	.967	1.442
N of Valid Cases	224		

Figure 98. The relationship between building use and residential burglaries (Source: Author).

Corner or middle lot. The results of chi-square statistics indicated a statistically significant difference between being a corner or middle lot dwelling and burglary occurrence (χ^2 = 5.03, df = 1, p = 0.03). The odds of burglary occurrence in middle lot residences was 0.48 times the odds of burglary occurrence in corner lot dwellings (OR = 0.48, 95% CI = 0.25-0.92). Further, the risk of burglary occurrence was reduced by 59% in middle lot buildings compared to corner lot residences (RR = 0.61, 95% CI = 0.40-0.93) (See *Figure 99*).

			FIRST_OFFENCE_14		
			Burglarized	Not Burglarized	Total
CornerMiddle_Coded	Middle and T Lot	Count	40	128	168
		Expected Count	46.5	121.5	168.0
		% of Total	17.9%	57.1%	75.0%
	Corner Lot	Count	22	34	56
		Expected Count	15.5	40.5	56.0
		% of Total	9.8%	15.2%	25.0%
Total		Count	62	162	224
		Expected Count	62.0	162.0	224.0
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	5.025[a]	1	.025		
Continuity Correction[b]	4.282	1	.039		
Likelihood Ratio	4.809	1	.028		
Fisher's Exact Test				.038	.021
N of Valid Cases	224				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 15.50.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for CornerMiddle_Coded (Middle and T Lot / Corner Lot)	.483	.254	.919
For cohort FIRST_OFFENCE_14 = Burglarized	.606	.397	.925
For cohort FIRST_OFFENCE_14 = Not Burglarized	1.255	1.000	1.575
N of Valid Cases	224		

Figure 99. The relationship between being a corner or middle lot and residential burglaries (Source: Author).

Vacant lot. The results of chi-square statistics indicated an insignificant relationship between adjacency to a vacant lot and burglary occurrence ($\chi^2 = 1.24$, df = 1, Fisher's exact p value > 0.05) (See *Figure 100*).

			FIRST_OFFENCE_14		
			Burglarized	Not Burglarized	Total
Adjacent_Vacant_Coded	No	Count	57	155	212
		Expected Count	58.7	153.3	212.0
		% of Total	25.4%	69.2%	94.6%
	Yes	Count	5	7	12
		Expected Count	3.3	8.7	12.0
		% of Total	2.2%	3.1%	5.4%
Total		Count	62	162	224
		Expected Count	62.0	162.0	224.0
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.239[a]	1	.266	.320	.212
Continuity Correction[b]	.611	1	.434		
Likelihood Ratio	1.148	1	.284	.320	.212
Fisher's Exact Test				.320	.212
N of Valid Cases	224				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 3.32.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Adjacent_Vacant_Coded (No / Yes)	.515	.157	1.687
For cohort FIRST_OFFENCE_14 = Burglarized	.645	.319	1.306
For cohort FIRST_OFFENCE_14 = Not Burglarized	1.253	.772	2.036
N of Valid Cases	224		

Figure 100. The relationship between adjacency to vacant lots and residential burglaries (Source: Author).

Maintenance. The results of chi-square statistics indicated an insignificant relationship between maintenance and burglary occurrence ($\chi^2 = 0.19$, df = 1, $p > 0.05$) (See *Figure 101*).

			FIRST_OFFENCE_14		
			Burglarized	Not Burglarized	Total
Maintenance_Coded	No	Count	33	81	114
		Expected Count	31.6	82.4	114.0
		% of Total	14.7%	36.2%	50.9%
	Yes	Count	29	81	110
		Expected Count	30.4	79.6	110.0
		% of Total	12.9%	36.2%	49.1%
Total		Count	62	162	224
		Expected Count	62.0	162.0	224.0
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.187[a]	1	.666		
Continuity Correction[b]	.080	1	.777		
Likelihood Ratio	.187	1	.666		
Fisher's Exact Test				.765	.389
N of Valid Cases	224				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 30.45.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Maintenance_Coded (No / Yes)	1.138	.633	2.045
For cohort FIRST_OFFENCE_14 = Burglarized	1.098	.718	1.679
For cohort FIRST_OFFENCE_14 = Not Burglarized	.965	.821	1.135
N of Valid Cases	224		

Figure 101. The relationship between maintenance and residential burglaries (Source: Author).

No-trespassing symbols. The results of chi-square statistics indicated an insignificant relationship between availability of no-trespassing signs and burglary occurrence ($\chi^2 = 3.12$, df = 1, $p > 0.05$) (See *Figure 102*).

			FIRST_OFFENCE_14		
			Burglarized	Not Burglarized	Total
Tresspassing_Sign_Coded	No	Count	50	145	195
		Expected Count	54.0	141.0	195.0
		% of Total	22.3%	64.7%	87.1%
	Yes	Count	12	17	29
		Expected Count	8.0	21.0	29.0
		% of Total	5.4%	7.6%	12.9%
Total		Count	62	162	224
		Expected Count	62.0	162.0	224.0
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.124[a]	1	.077		
Continuity Correction[b]	2.387	1	.122		
Likelihood Ratio	2.921	1	.087		
Fisher's Exact Test				.117	.064
N of Valid Cases	224				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 8.03.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval Lower	95% Confidence Interval Upper
Odds Ratio for Tresspassing_Sign_Coded (No / Yes)	.489	.218	1.094
For cohort FIRST_OFFENCE_14 = Burglarized	.620	.378	1.016
For cohort FIRST_OFFENCE_14 = Not Burglarized	1.268	.924	1.741
N of Valid Cases	224		

Figure 102. The relationship between availability of no-trespassing signs and residential burglaries (Source: Author).

Diversity. The results of chi-square statistics indicated an insignificant relationship between presence or absence of non-residential facilities within 49 ($\chi^2 = 0.96$, df = 1, Fisher's exact p value > 0.05), 95 ($\chi^2 = 1.96$, df = 1, $p > 0.05$) and 141 ($\chi^2 = 0.20$, df = 1, $p > 0.05$) feet of buildings and burglary occurrence (See *Figure 103*, *Figure 104* and *Figure 105*).

			FIRST_OFFENCE_14		
			Burglarized	Not Burglarized	Total
Facilities49_Coded	No	Count	61	155	216
		Expected Count	59.8	156.2	216.0
		% of Total	27.2%	69.2%	96.4%
	Yes	Count	1	7	8
		Expected Count	2.2	5.8	8.0
		% of Total	0.4%	3.1%	3.6%
Total		Count	62	162	224
		Expected Count	62.0	162.0	224.0
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.955[a]	1	.328	.449	.299
Continuity Correction[b]	.330	1	.565		
Likelihood Ratio	1.111	1	.292	.449	.299
Fisher's Exact Test				.449	.299
N of Valid Cases	224				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 2.21.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Facilities49_Coded (No / Yes)	2.755	.332	22.862
For cohort FIRST_OFFENCE_14 = Burglarized	2.259	.357	14.306
For cohort FIRST_OFFENCE_14 = Not Burglarized	.820	.623	1.080
N of Valid Cases	224		

Figure 103. The relationship between diversity and residential burglaries within 49 feet of buildings (Source: Author).

			FIRST_OFFENCE_14		
			Burglarized	Not Burglarized	Total
Facilities141_Coded	No	Count	41	102	143
		Expected Count	39.6	103.4	143.0
		% of Total	18.3%	45.5%	63.8%
	Yes	Count	21	60	81
		Expected Count	22.4	58.6	81.0
		% of Total	9.4%	26.8%	36.2%
Total		Count	62	162	224
		Expected Count	62.0	162.0	224.0
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.195[a]	1	.659		
Continuity Correction[b]	.082	1	.775		
Likelihood Ratio	.196	1	.658		
Fisher's Exact Test				.756	.390
N of Valid Cases	224				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 22.42.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Facilities141_Coded (No / Yes)	1.148	.621	2.124
For cohort FIRST_OFFENCE_14 = Burglarized	1.106	.705	1.734
For cohort FIRST_OFFENCE_14 = Not Burglarized	.963	.816	1.136
N of Valid Cases	224		

Figure 104. The relationship between diversity and residential burglaries within 95 feet of buildings (Source: Author).

			FIRST_OFFENCE_14		
			Burglarized	Not Burglarized	Total
Facilities95_Coded	No	Count	55	131	186
		Expected Count	51.5	134.5	186.0
		% of Total	24.6%	58.5%	83.0%
	Yes	Count	7	31	38
		Expected Count	10.5	27.5	38.0
		% of Total	3.1%	13.8%	17.0%
Total		Count	62	162	224
		Expected Count	62.0	162.0	224.0
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.959[a]	1	.162		
Continuity Correction[b]	1.442	1	.230		
Likelihood Ratio	2.096	1	.148		
Fisher's Exact Test				.232	.113
N of Valid Cases	224				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 10.52.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Facilities95_Coded (No / Yes)	1.859	.772	4.476
For cohort FIRST_OFFENCE_14 = Burglarized	1.605	.793	3.248
For cohort FIRST_OFFENCE_14 = Not Burglarized	.863	.723	1.031
N of Valid Cases	224		

Figure 105. The relationship between diversity and residential burglaries within 141 feet of buildings (Source: Author).

Facing of buildings. The results of chi-square statistics indicated an insignificant relationship what type of streets dwellings face and burglary occurrence ($\chi^2 = 2.87$, df = 1, $p > 0.05$) (See *Figure 106*).

			FIRST_OFFENCE_14		
			Burglarized	Not Burglarized	Total
Bldg_Face_Coded	Regional	Count	45	134	179
		Expected Count	49.5	129.5	179.0
		% of Total	20.1%	59.8%	79.9%
	Neighborhood Collector	Count	17	28	45
		Expected Count	12.5	32.5	45.0
		% of Total	7.6%	12.5%	20.1%
Total		Count	62	162	224
		Expected Count	62.0	162.0	224.0
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	2.869[a]	1	.090		
Continuity Correction[b]	2.273	1	.132		
Likelihood Ratio	2.741	1	.098		
Fisher's Exact Test				.097	.068
N of Valid Cases	224				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 12.46.

b. Computed only for a 2x2 table

Risk Estimate

	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for Bldg_Face_Coded (Regional / Neighborhood Collector)	.553	.277	1.104
For cohort FIRST_OFFENCE_14 = Burglarized	.665	.423	1.046
For cohort FIRST_OFFENCE_14 = Not Burglarized	1.203	.944	1.534
N of Valid Cases	224		

Figure 106. The relationship between facing of buildings and residential burglaries (Source: Author).