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Crime and Greenspace: Extending the Analysis Across Cities

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CRIME AND GREENSPACE: EXTENDING THE ANALYSIS ACROSS CITIES

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ABSTRACT

The role of greenspace in urban areas has become a focus of research as municipalities seek to increase the quality of life in cities. Multiple benefits are found to be associated with greenspace, but disservices such as crime are often overlooked. Studies investigating the link between crime and greenspace have revealed mixed results and been limited in geographic scope. This dissertation sought to examine the crime and greenspace relationship, extending the analysis to multiple cities in order to describe how the relationship may vary in different contexts. Additionally, one possible cause of crime, increased temperatures, was investigated to determine how greenspace may moderate the impact of hot weather on crime risk. As urban parks are an important type of greenspace, the relationship between proximity to parks and crime was examined in four case cities. Parks are typically green areas of cities but also encompass less green land uses. This broad analysis revealed a more comprehensive understanding of how crime and greenspace are related which can inform residents and decision-makers of the benefits and possible drawbacks from including greenspace in city and community development.

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CHAPTER ONE

Problem Statement

The world's population has become majority urban and the number of people living in cities is expected to continue to grow (United Nations, 2015). These urban areas face many challenges as they plan for the well-being of current and future residents (Childers, Pickett, Grove, Ogden, & Whitmer, 2014; Pickett & Cadenasso, 2006). One component of a quality living environment is greenspace, which is seen as providing numerous benefits to cities (Kabisch, Qureshi, & Haase, 2015; Larson, Jennings, & Cloutier, 2016). However, such interventions as natural areas or parks may have negative, as well and positive, impacts on people in the city (Escobedo et al., 2018; von Döhren & Haase, 2015).

Many benefits have been identified with greenspace in the city. Encouraging greater physical activity (Bedimo-Rung, Mowen, & Cohen, 2005; Kaczynski, Potwarka, & Saelens, 2008), reducing the prevalence of obesity (Alexander, Huber, Piper, & Tanner, 2013), and improving overall physical and mental health (Besenyi et al., 2014; Tsai et al., 2018) are some ways that greenspace may increase the well-being of residents. For the community, greenspace is associated with greater social connections (Maas, van Dillen, Verheij, & Groenewegen, 2009) and increasing collective efficacy (Cohen, Inagami, & Finch, 2008).

Despite the benefits, greenspaces and parks have also been seen as leading to disturbance of the local community, such as providing concealment for criminal activity and limiting visibility (Mak & Jim, 2018; Michael, Hull, & Zahm, 2001). Outsiders and a lack of oversight can be seen as inviting minor to major criminal behavior. Researchers have attempted to investigate the tie between urban greenspaces and crime in a small number of cities and using various methods (Bogar & Beyer, 2016). However, a more comprehensive approach has not been taken that could lend evidence to how greenspaces and crime might be related. This dissertation seeks to address gaps in this topic by extending work on the relationship between greenspace and crime and how that relationship may function in regards to weather and type of greenspace.

What is greenspace?

One important concept in this dissertation is that of *greenspace*. This term has multiple meanings depending on the research and planning context (Taylor & Hochuli, 2017). In a broad sense, it covers all green vegetation in the landscape. In this perspective both planned and unplanned land uses can be greenspace. Gardens, parks, vacant lots, and riparian areas can all be part of urban greenspace. In many cases though, greenspace is defined by example, with the most common form given by researches being parks (Taylor & Hochuli, 2017).

The impact of greenspace is often explored through the broad form of all green vegetation. This is the approach used when greenspace is assessed through aerial or satellite imagery, using a measure called normalized difference vegetation index (NDVI). Research in public health has often used NDVI as it provides an efficient means of measuring greenness at various spatial scales (Markevych et al., 2017). Other methods of greenspace assessment have included ground-based tools and digital data such as Google

StreetView imagery (Bader, Mooney, Bennett, & Rundle, 2016; Bedimo-Rung, Gustat, Tompkins, Rice, & Thomson, 2006; Gidlow et al., 2017). These ground level tools seek to better describe green vegetation in terms of type, structure, or quality.

Urban greenspace is also defined by types of land use. Parks, gardens, vacant lots, and forests are often used in research on urban greenspaces (Taylor & Hochuli, 2017). These land use types entail more than just vegetation, but also imply management and ownership of areas that allow for vegetation within the city (Forsyth, Musacchio, & Fitzgerald, 2005; Rigolon, Browning, & Jennings, 2018; Taylor & Hochuli, 2017).

In this dissertation urban greenspace will be explored in two forms. The first is the general concept of greenspace being all green vegetation. The second form investigated will be urban parks, which may or may not be green vegetated spaces, but are often referenced as a key example of greenspace in the city.

Purpose Statement

The components of this dissertation are intended to address gaps in the research regarding the relationship between urban greenspace and crime. The overall purpose of this dissertation is to examine how urban greenspace, as well as urban parks, are related to crime. Greenspace was analyzed in both a general form of all green vegetation and a specific form of urban parks. Guiding the inquiry were the following research objectives:

1. To examine the relationship between urban greenspace and crime and how the relationship varies across cities.
2. To examine if greenspace functions as a moderator between temperature and crime.

3. To examine how proximity of neighborhoods to urban parks relates to crime in different city contexts.

Urban greenspace can have beneficial impacts for cities, but disservices such as crime are not well understood (Bogar & Beyer, 2016). An improved understanding of how greenspace and crime are related can help uncover if these land uses have any negative impacts that should be considered in planning and design. For greenspace that is in the form of urban parks, the care of existing parks and location of future parks will require a full understanding of how these spaces may impact local communities and the larger city in order to ensure benefits and costs are equitably distributed among residents.

Document Structure

The dissertation consists of three manuscripts intended for publication in peer-reviewed journals. The first manuscript explored the general relationship between urban greenspace and crime. This extended prior research by examining this association across cities with population over 100,000 in the US. As green vegetation is related to climate conditions, a measure of city climate will be included, a factor that has not been used in other research. The target journal for this chapter could be the Proceedings of the National Academy of Sciences (PNAS).

The second manuscript examined how urban greenspace may moderate the relationship between weather and crime. Temperature has been viewed as a cause of increased crime and greenspace has been suggested as a way to reduce urban temperatures. This study used a measure of thermal comfort to examine how urban greenspace may moderate the relationship between temperature and crime in cities. This chapter could be targeted for publication in Global Environmental Change.

The third manuscript focused on urban parks as a specific type of greenspace. Four case cities were selected to examine how parks are related to crime using detailed data on crimes and land use within each city. Publication of this chapter can be aimed at the journal Landscape and Urban Planning.

References

Alexander, D. S., Huber, L. R. B., Piper, C. R., & Tanner, A. E. (2013). The association between recreational parks, facilities and childhood obesity: a cross-sectional study of the 2007 National Survey of Children's Health. *Journal of Epidemiology and Community Health*, *67*(5), 427–431.

Bader, M. D. M., Mooney, S. J., Bennett, B., & Rundle, A. G. (2016). The Promise, Practicalities, and Perils of Virtually Auditing Neighborhoods Using Google Street View. *The Annals of the American Academy of Political and Social Science*, *669*(1), 18–40.

Bedimo-Rung, A. L., Gustat, J., Tompkins, B. J., Rice, J., & Thomson, J. (2006). Development of a Direct Observation Instrument to Measure Environmental Characteristics of Parks for Physical Activity. *Journal of Physical Activity & Health*, *3*(s1), S176–S189.

Bedimo-Rung, A. L., Mowen, A. J., & Cohen, D. (2005). The significance of parks to physical activity and public health: A conceptual model. *American Journal of Preventive Medicine*, *28*(2, Supplement 2), 159–168.

Besenyi, G. M., Kaczynski, A. T., Stanis, S. A. W., Bergstrom, R. D., Lightner, J. S., & Hipp, J. A. (2014). Planning for health: a community-based spatial analysis of park availability and chronic disease across the lifespan. *Health & Place*, *27*, 102–105.

Bogar, S., & Beyer, K. M. (2016). Green Space, Violence, and Crime: A Systematic Review. *Trauma, Violence & Abuse*, *17*(2), 160–171.

Childers, D. L., Pickett, S. T. A., Grove, J. M., Ogden, L., & Whitmer, A. (2014). Advancing urban sustainability theory and action: Challenges and opportunities. *Landscape and Urban Planning*, *125*, 320–328.

Cohen, D., Inagami, S., & Finch, B. (2008). The built environment and collective efficacy. *Health & Place*, *14*(2), 198–208.

Escobedo, F. J., Clerici, N., Staudhammer, C. L., Feged-Rivadeneira, A., Bohorquez, J. C., & Tovar, G. (2018). Trees and Crime in Bogota, Colombia: Is the link an ecosystem disservice or service? *Land Use Policy*, *78*, 583–592.

Forsyth, A., Musacchio, L., & Fitzgerald, F. (2005). *Designing Small Parks: A Manual for Addressing Social and Ecological Concerns*. John Wiley & Sons.

Gidlow, C., van Kempen, E., Smith, G., Triguero, M., Kruize, H., Gražulevičienė, R., … Nieuwenhuijsen, M. J. (2017). Development of the Natural Environment Scoring Tool (NEST). *Urban Forestry & Urban Greening, 29*, 322-333.

Kabisch, N., Qureshi, S., & Haase, D. (2015). Human–environment interactions in urban green spaces — A systematic review of contemporary issues and prospects for future research. *Environmental Impact Assessment Review*, *50*, 25–34.

Kaczynski, A. T., Potwarka, L. R., & Saelens, B. E. (2008). Association of park size, distance, and features with physical activity in neighborhood parks. *American Journal of Public Health*, *98*(8), 1451–1456.

Larson, L. R., Jennings, V., & Cloutier, S. A. (2016). Public Parks and Wellbeing in Urban Areas of the United States. *PloS One*, *11*(4), e0153211.

Maas, J., van Dillen, S. M. E., Verheij, R. A., & Groenewegen, P. P. (2009). Social contacts as a possible mechanism behind the relation between green space and health. *Health & Place*, *15*(2), 586–595.

Mak, B., & Jim, C. Y. (2018). Examining fear-evoking factors in urban parks in Hong Kong. *Landscape and Urban Planning*, *171*, 42–56.

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., … Fuertes, E. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research*, *158*, 301–317.

Michael, S. E., Hull, R. B., & Zahm, D. L. (2001). Environmental factors influencing auto burglary A case study. *Environment and Behavior*, *33*(3), 368–388.

Pickett, S. T. A., & Cadenasso, M. L. (2006). Advancing urban ecological studies: Frameworks, concepts, and results from the Baltimore Ecosystem Study. *Austral Ecology*, *31*(2), 114–125.

Rigolon, A., Browning, M., & Jennings, V. (2018). Inequities in the quality of urban park systems: An environmental justice investigation of cities in the United States. *Landscape and Urban Planning*, *178*, 156–169.

Taylor, L., & Hochuli, D. F. (2017). Defining greenspace: Multiple uses across multiple disciplines. *Landscape and Urban Planning*, *158*, 25–38.

Tsai, W.-L., McHale, M. R., Jennings, V., Marquet, O., Hipp, J. A., Leung, Y.-F., & Floyd, M. F. (2018). Relationships between Characteristics of Urban Green Land Cover and Mental Health in U.S. Metropolitan Areas. *International Journal of Environmental Research and Public Health*, *15*(2).

United Nations. (2015). Cities - United Nations Sustainable Development Action 2015. Retrieved November 5, 2017, from United Nations Sustainable Development Goals - Time for Global Action for People and Planet website: http://www.un.org/sustainabledevelopment/cities/

von Döhren, P., & Haase, D. (2015). Ecosystem disservices research: A review of the state of the art with a focus on cities. *Ecological Indicators*, *52*, 490–497.

CHAPTER TWO

MORE GREEN LESS CRIME? THE CRIME AND GREENSPACE RELATIONSHIP ACROSS 301 CITIES

Abstract

Greenspace provides numerous quality of life benefits to urban residents, including areas for physical activity and aiding in mental health. Despite these benefits, greenspace can also attract crime and provide cover for criminals. To investigate the relationship between crime and greenspace and extend the examination to a wide-range of city contexts, Iused a multilevel modeling approach to examine census block group-level data in 301 cities in the United States. After accounting for potential covariates of crime, including socioeconomic and climate variables, more greenspace was associated with less property crime risk in block groups within all cities. Violent crime risk also exhibited the same relationship, with only three cities having more greenspace in block groups associated with increased violent crime risk. In general, higher amounts of greenspace were associated with lower crime risk. Further research could investigate links between crime and specific types and seasonal variations of greenspace.

Introduction

Urban greenspace can be a key component of the city landscape, bringing benefits to residents through physical activity, restoration, and improved health (Kaczynski, Potwarka, & Saelens, 2008; Kaplan, 1995; Sugiyama, Carver, Koohsari, & Veitch, 2018; Tsai et al., 2018). However, negative outcomes of greenspace are often overlooked (Crewe, 2001), with exacerbated crime being one detrimental consequence of concern within many communities (Branas, Rubin, & Guo, 2013; Keith, Larson, Shafer, Hallo, & Fernandez, 2018; Sreetheran & van den Bosch, 2014).

Previous research has attempted to understand how greenspace may be associated with crime, but this research has focused on a handful of case study locations rather than describing how this relationship may vary across cities. If there are negative associations between crime and greenspace in one city, would those same associations exist in other cities? Additionally, while prior work has included common covariates of crime, such as income and family composition, variables that influence the amount of green vegetation, such as climate, have not been accounted for (Tsai et al., 2018). The amount of green vegetation in block groups within a city is strongly influenced by climatic factors of the region a city is situated in, such as precipitation and temperature (Kreft & Jetz, 2007; Stephenson, 1990). The objective of this study was to identify how greenspace and crime may be related at the block group level across 301 U.S. cities with populations over 100,000 in order to better describe the crime and greenspace relationship. Specifically, this study examined the following research questions:

How are urban greenspace and crime related at the local level of census block groups?

How does this relationship vary across cities?

Background

Greenspace is considered to be one aspect of the environment that has an influence on crime (Kimpton, Corcoran, & Wickes, 2017). Research has focused on violent crime due to the perspective that vegetation reduces aggression by providing mental restoration (Branas et al., 2018; Kuo & Sullivan, 2001a). To a lesser degree, property crime has also been investigated (Chen, Li, & Li, 2016; Ye, Chen, & Li, 2018). Across studies the methods and findings have varied, with improved methodology and comparisons of local conditions between cities called for as a means of investigating the relationship further (Bogar & Beyer, 2016; Mancus & Campbell, 2018).

Crime and Greenspace

A number of studies have investigated how crime and greenspace may be related due to crime and the fear of crime being a barrier to greenspace development and use (Sreetheran & van den Bosch, 2014). The term 'greenspace' is not clearly defined within the literature (Taylor & Hochuli, 2017). In the current study, greenspace is considered to be all green vegetation assessed through remotely sensed imagery from satellites. This technique and definition is commonly used in research on urban greenspace and its relationship with human behavior and health (Beyer et al., 2014; Gascon et al., 2016; Markevych et al., 2017; Wolfe & Mennis, 2012).

Greenspace, viewed as all vegetated areas of a city, is found to be both a generator and a deterrent of crime. As a cause of crime, greenspace is seen as providing cover for criminals (Mak & Jim, 2018; Michael, Hull, & Zahm, 2001). Vegetation can also limit visibility which can lead to greater vulnerability to crime and lessen perceived safety of residents (Baran, Tabrizian, Zhai, Smith, & Floyd, 2018; Ceccato, 2014; Nasar, Fisher, & Grannis, 1993). Uncared for greenspace can communicate a lack of oversight and attract criminal activities (Nassauer, 1995; Sampson et al., 2017).

Other studies find greenspace associated with reductions in crime. An often-cited case is Kuo and Sullivan's (2001b) study of Chicago public housing which concluded that greater vegetation was associated with reduced crime among residents. Further research has aligned with these findings, extending the definition of what greenspace is, from vegetation in general to specific forms such as street trees (Donovan & Prestemon, 2010; Kondo, Han, Donovan, & MacDonald, 2017), vacant lots (Branas et al., 2011), and tree canopy (Gilstad-Hayden et al., 2015; Schusler, Weiss, Treering, & Balderama, 2017; Troy, Grove, & O'Neil-Dunne, 2012). In these studies, greater vegetation tends to correlate with decreases in crime. Only one study, in New Haven, CT, found no statistically significant difference in crime before and after a community greening program (Locke, Han, Kondo, Murphy-Dunning, & Cox, 2017).

Greenspace is found to be related to both lower crime and increased crime and fear of crime (Sreetheran & Van Den Bosch, 2014), but studies have varied in the crime covariates used, methods of measuring greenspace, and in scope. Many studies include some measure of income as a covariate of crime, while other variables such as education or residential characteristics are used sporadically. The assessment of greenspace has also varied, with some research measuring only street trees and others using aerial or satellite imagery (i.e. percent area in tree canopy (Schusler et al., 2017) and qualitative vegetation rating (Kuo & Sullivan, 2001b). All existing work has focused on single cities and not attempted to examine how the relationship between greenspace and crime might differ for local areas across different contexts (Bogar & Beyer, 2016). The variety of methods used make it difficult to compare findings and gain a clearer understanding of the crime and greenspace relationship (Bogar & Beyer, 2016). This study seeks to incorporate a broad sample of cities to extend the understanding of crime and greenspace at the local level across city contexts.

Methods

To explore how greenspace and crime are related, data were collected at the census block group and city level for 301 cities with populations over 100,000 in the conterminous United States for 2015 (see Appendix A). The unit of analysis was census block groups, the smallest geographical unit for which the US Census Bureau collects detailed sociodemographic data. Due to the nested nature of the data, with block groups nested within cities, Iused a multilevel modeling approach in order to estimate the relationship between greenspace and crime across all cities in the study and produce population and city level estimates of how greenspace and crime are related. A dataset was created for 59,703 block groups across 301 cities.

Data were sourced from the US Census Bureau to determine the sample cities based on population. Values for sociodemographic variables were retrieved from the 2011-2015 American Community Survey (ACS) 5-year estimates for census block groups in R software using the *tidycensus (0.4.6)* package (Walker, 2018). Spatial data were retrieved from Census Bureau TIGER geodatabases for cities, using the census designation of 'places', which are incorporated municipalities. Iselected block groups that were greater than 50% within city boundaries.

Greenspace was measured from satellite imagery for 2015. These greenspace values were combined with the sociodemographic data into a full dataset of block group and city variables. Description and sources for the variables are presented in table 2.2.

Table 2.1. Data description and sources

Variable	Description	Source
NDVI (greenspace)	Mean value of 30m pixels in block group	Landsat 8
Median Household Income	In 1,000's dollars	ACS
Percent under 18	Percent of population under 18	ACS
Population density	Number of residents per square kilometer	ACS
Disadvantage Index	Measure of social disadvantage in block group	ACS
Percent unemployed	Percent of population over 16 unemployed	ACS
Percent less than a high school	Percent of population over 25 with less than a high school diploma	ACS
Percent female headed	Percent of households that are female headed	ACS
Percent families below poverty	Percent of families below poverty	ACS
Diversity Index	Index of racial diversity in block group	ACS
Crime Risk Index	Crime rate indexed relative to national average	Esri
Crime Rate	Number of crimes per 1,000 population	FBI
Police Force	Number of officers per 1,000 population	FBI
Climate Region	Classified climate region	PRISM
GDP	Per capita GDP for Metropolitan Statistical Area, in 1,000's dollars	BEA

ACS - American Community Survey 2011-2015 5-year Estimates

Esri, Inc. - Demographics 2016

FBI - Federal Bureau of Investigation, Crime in the United States 2015

PRISM - PRISM Climate Group (http://www.prism.oregonstate.edu/)

BEA - Bureau of Economic Analysis (https://www.bea.gov/data/gdp/gdp-metropolitan-area)

Dependent Variable – Crime Risk Index

Crime risk data for census block groups was sourced from Esri, Inc. who provide data on the relative crime risk of various geographic areas (Esri, 2016). The measurement is an index of crime risk and has been used in similar work on crime and greenspace by Troy and Grove (2008). The index is based on a value of 100 being the national average crime risk, so that a value of 200 would represent twice the national average. The data are provided in 10 categories that align with Federal Bureau of Investigation (FBI) Uniform

Crime Report (UCR) Part 1 crimes, covering violent and property crimes (Federal Bureau of Investigation, 2004). The study used two crime risk types of all violent crime and all property crime as the dependent variable. Violent crime is composed of assault, murder, robbery crimes while property crime is composed of burglary, larceny, and auto theft.

Level 1 independent variables – block group characteristics

Greenspace - Greenspace was operationalized as the mean normalized difference vegetation index (NDVI) for a block group obtained from satellite imagery. NDVI provides a measure of vegetation using different wavelengths of light reflected by plants, and is a common measure of greenspace used in research across different domains (Browning, Kuo, Sachdeva, Lee, & Westphal, 2018; Gascon et al., 2016; Markevych et al., 2017). Many other indices are available to assess vegetation from remotely sensed imagery, but the ease of calculating NDVI has made it popular as a measure of local greenness and greenspace. NDVI is found to be a suitable proxy for greenspace based on comparison with expert input and provides an objective assessment of neighborhood conditions (Gascon et al., 2016; Rhew, Vander Stoep, Kearney, Smith, & Dunbar, 2011). The value for NDVI was calculated based on Landsat 8 imagery for 2015 using the Google Earth Engine platform (Gorelick et al., 2017). Values for NDVI range from -1 to +1 and roughly translate to bare soil, water, or impervious surfaces below 0.1, grasses and shrubs from 0.2 to 0.5, and dense vegetation and forest above 0.6 (Weier & Herring, 2000). NDVI was transformed by multiplying the values by 10 to convert the unitless range from -1:1 to -10:10, so that interpretation of regression results will be more meaningful (1-unit change would be equal to a 0.1 change in NDVI).

Sociodemographic Covariates - Sociodemographic variables were obtained at the block group level. These variables represent the social conditions of an area and are found to be related to crime in prior research (Land, McCall, & Cohen, 1990; Sampson, Morenoff, & Gannon-Rowley, 2002). The data used was from the 2012-2015 5-year American Community Survey (ACS), which provides demographic sample-based estimates between the decennial census at the census block group level. The variables used were: 1) median household income, 2) disadvantage index, 3) diversity index, 4) percent under 18, and 5) log population density. The disadvantage index and diversity index capture variables related to the social disadvantage of an area and its mix of racial groups.

Disadvantage Index - As social disadvantage is associated with crime in the literature, an index was created from other demographic variables (Bursik, 1988; Kubrin & Weitzer, 2003; Sampson & Groves, 1989). This index composes a factor that represents area disadvantage for census block groups (Sampson, Raudenbush, & Earls, 1997). The disadvantage index was created from the mean z-score of: 1) percentage unemployed, 2) percentage of families below poverty, 3) percentage with less than high school education, and 4) percentage of households that are female headed with no husband (Krivo, Peterson, & Kuhl, 2009). The resulting score indicates if a block group is more or less disadvantaged than the average block group in the study.

Diversity Index - The diversity index was constructed from the percentage of the population in each of the 14 racial and ethnic groups recorded in the ACS (Cassal, 2018). This value is based on Simpson's index, a diversity index often used in ecological studies

(Simpson, 1949). Simpson's index provides the probability of two randomly selected individuals being from the same group and ranges from 0 (homogeneous) to 1 (heterogeneous), representing the degree of racial and ethnic diversity in the block group.

Level 2 independent variables – city context

Crime - Crime data was collected at the city level from the FBI UCR to provide an overall measure of crime in each city context, which serves as a large scale view of crime in each city that could explain local crime risk (McDowall & Loftin, 2009). Counts of the number of offenses and population were obtained for all cities (Federal Bureau of Investigation, 2016). Using these counts, a rate per 1,000 persons was calculated for 2015 for violent and property crimes.

Police force - The size of city police forces is found to the associated with crime in prior research (Levitt, 1997). For this reason, the size of the municipal law enforcement agency was used as a measure of the level of policing that exists in a city. The number of officers was obtained from FBI law enforcement employment data for 2015 and divided by the city population (Federal Bureau of Investigation, 2016). This police force variable is the number of officers per 1,000 persons. Some cities were found to contract out law enforcement to county agencies. In such cases, the police force rate for the area served by a county law enforcement agency was used for the city.

GDP - The economic condition of a city is one contextual variable that is thought to contribute to crime (Andresen, 2015). To account for differences in the economic context of cities, the per capita metropolitan gross domestic product (GDP) was obtained from the Bureau of Economic Analysis. GDP is calculated for metropolitan regions and provides a measure of "the value of the goods and services produced" within an area (U S Department of Commerce, 2015).

Climate type - The city's climatic region has a direct effect on the amount and type of vegetation that can grow there (Grace, 2008). It is key to define climate as the long-term trend and variability of weather conditions, different than weather at a specific time (IPCC, 2014). Researchers have suggested that a measure of climate be included in future greenspace research (Tsai et al., 2018). One way that climate can be incorporated in the analysis is through classification based on temperature and precipitation. These measures form the basis for the Köppen-Geiger classification, a widely used global climate classification system (Peel, Finlayson, & McMahon, 2007). As this study is focused only on the contiguous U.S., the Köppen-Geiger classification did not provide adequate differentiation for the sample cities. As an alternative, a k-means clustering approach was taken that used 1) mean 30-year temperature, 2) mean 30-year precipitation, and 3) mean number of days above 90ºF to group cities into four categories using the *kmeans* function in R statistical software version 3.5.0 (PRISM climate group, n.d.; R Core Team, 2017). The four regions are conceptualized as being a combination of temperature, precipitation, and days above 90ºF - region 1: cool-dry-low, region 2: cool-wet-low, region 3: warm-dry-high, and region 4: warm-wet-high (see figure 2.1 and table 2.1).

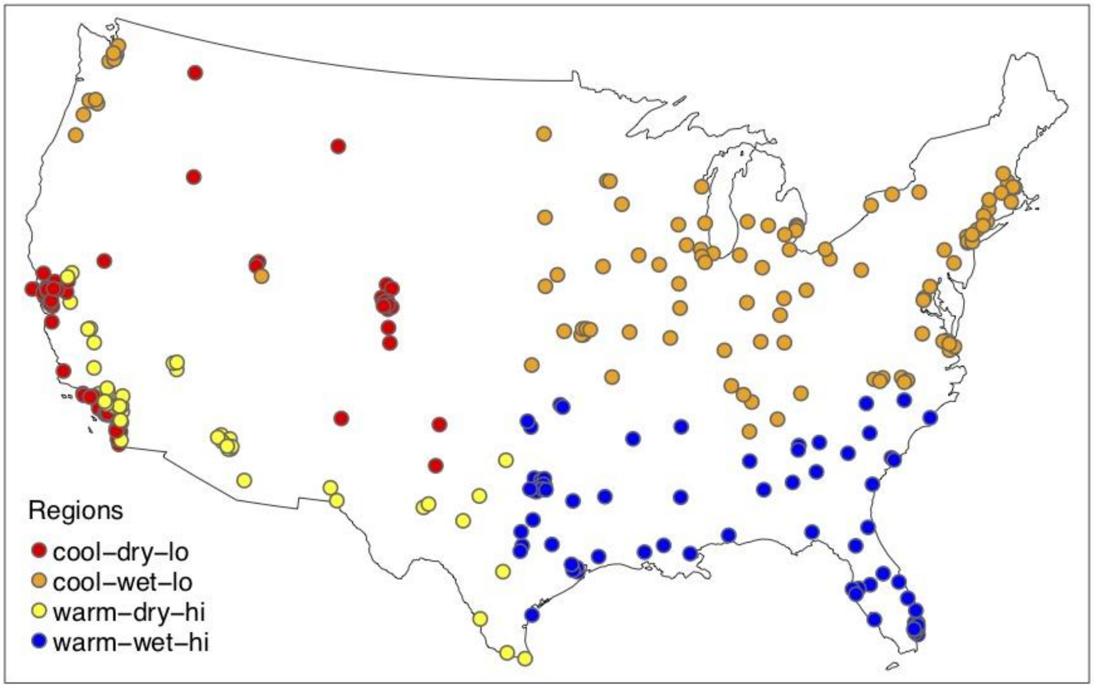

Figure 2.1. City locations and climate classification

Table 2.2. Climate region descriptive statistics

Cluster Name	Mean Annual Temperature (ºF)	Mean Annual Precipitation (in)	Mean Maximum Temperature	Mean Minimum Temperature	Mean Temperature Range	Mean NDVI	Mean Number of days above 90ºF
cool-dry-high	58.4	16.4	83.8	35.8	80.0	0.343	27
cool-wet-low	52.8	41.3	84.6	22.0	94.5	0.540	16
warm-dry-high	66.5	13.8	97.3	39.0	90.2	0.292	108
warm-wet-high	67.8	48.5	92.4	41.0	83.4	0.526	81

Analysis

Initially a bivariate analysis of Pearson's product moment correlation was performed to test for significant associations between crime risk, greenspace, and the chosen covariates. The dependent variable in the modeling was the crime risk index value in the census block group, for violent and property crime. The independent variables at the block group level were: mean NDVI, median household income, percent of population under 18 years, population density (log), disadvantage index, and diversity index. At the city level, the independent variables are: crime rate per 1,000 population, police officers per 1,000 population, climate region, and per capita GDP.

Following the suggestion of Hox (2010), statistical models were built from simple to more complex. The initial intercept-only null model, model 1, allowed for the determination of variability attributable to cities. All variables were grand mean centered to allow interpretation in reference to the average for each variable across all block groups in the study, with 0 being the mean value for the variable. Model 2 included level 1, or block group variables. Model 3 added level 2, or city variables, including climate region.

Linear multilevel models were fit in R statistical software using the *lmer4* package (Bates, Mächler, Bolker, & Walker, 2015). Models were compared to the baseline model with the Akaike information criterion (AIC) and Likelihood Ratio Test (LRT) to determine if additional variables improved model fit. A measure of variance "explained' by the models was calculated as the correlation of the predicted and observed values of the response variable to provide an overall pseudo-R^2 value for each model (Aguinis, Gottfredson, & Culpepper, 2013; Singer & Willett, 2003).

Both random intercepts and random slopes were specified in the modeling. Random intercepts for the dependent variable of crime risk allow for separate estimates of the mean block group crime risk values for the cities. The random slope of NDVI allows an estimate of the relationship between block group NDVI and crime to vary across cities.

Model Descriptions

Model 1(null model): *crime risk = 1 + (1|city)*

Model 2: *model 1 + NDVI + median income + under 18 + disadvantage index + diversity index + population density + (NDVI | city)*

Model 3: *model 2 + police force + crime rate + per capita GDP*

Model 4: *model 3 + climate region*

Results

Census Block Groups

The sample included 62,086 census block groups that were greater than 50% within city boundaries by area. Missing values were present due to censoring of household income in block groups with low populations and block groups with no estimated population, resulting in 59,703 complete cases. Descriptive statistics for level one and level two units are provided in table 2.3.

Table 2.3. Descriptive statistics of census block groups and cities

Level	Variable	mean	sd	min	max
Level 1 - Census Block Group					
	Crime Risk Property	136	92.3	3	1,030
	Crime Risk Violent	180	162	2	1,334
	Disadvantage Index	0.05	0.791	-1.19	4.28
	Diversity Index	4.76	2.14	0	8.79
	Median Household Income (000's)	55.7	32.9	2.5	250
	Mean NDVI	4.07	1.52	0.514	8.06
	Percent Under 18	22.3	9.7	0	69.7
	Area (square kilometer)	1.05	3.47	0.00	223
	Total Population	1,444	846	23	22,054
	Population Density per Square Kilometer	5,610	9,882	4.18	220,955
Level 2 - City					
	Per Capita GDG (000's)	56.6	14.9	20.5	178
	Per Capita Police (per 1,000)	2.52	1.39	0.09	5.86
	Crime Rate - Property (per 1,000)	34.4	13.9	9.95	93.3
	Crime Rate - Violent (per 1,000)	6.91	3.75	0.51	18.2
	Population	1,530,178.87	2,483,657.21	98,312	8,550,405
	Population Density per Square Kilometer	7,243.68	7,762.06	615.86	28,363
	Number of Block Groups	198.16	408.47	28.00	5,858

Bivariate analysis

Correlations between the variables showed significant association between the crime risk index and covariates (figure 2.2). The strongest correlations existed between disadvantage and median income, and median income and violent crime risk. Total crime risk was highly correlated with the two crime subtypes and was excluded from further analysis. Violent crime risk was positively correlated with disadvantage, more so than property crime risk. Surprisingly, NDVI was positively correlated with violent and property crime risk, though weakly. Non-significant correlations existed between NDVI and median income, and percent under 18 and city violent crime rate per 1,000.

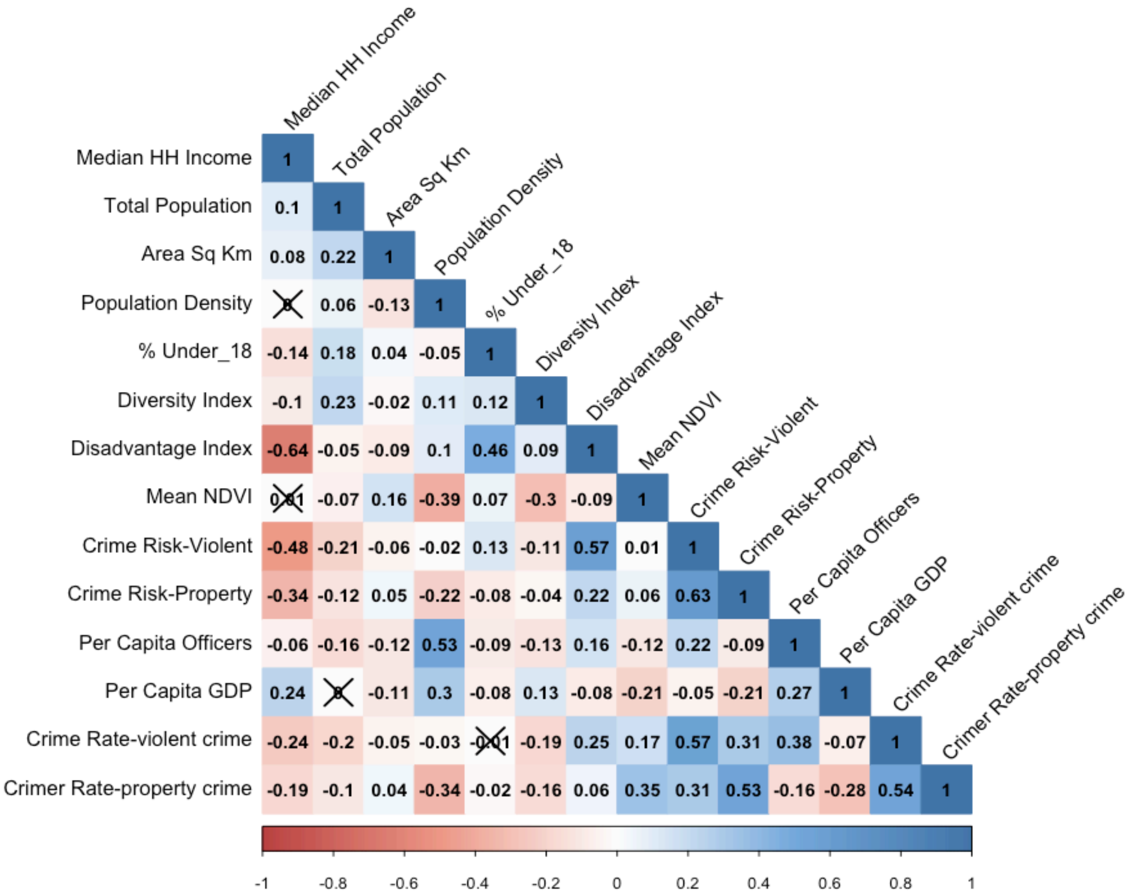

Figure 2.2. Correlation matrix. X cells indicate p > 0.05.

Model Results

The initial null model, model 1, provided the variance for the calculation of the intraclass correlation (ICC) value for violent crime (0.346), property crime (0.314), and the variable of interest, NDVI (0.686). The ICC indicated that there was variation in the block group crime variables and the greenspace measure of NDVI attributable to the city level, providing support for using a multilevel modeling approach. In the study, 34.6% of the variation in the violent crime risk index and 31.4% of the variation in the property crime risk index is due to differences between cities.

Model 2 introduced the level 1 (block group) variables of median household income, disadvantage index, diversity index, percent under 18, log population density, and mean NDVI. This model has a pseudo-R^2 of 0.326 for violent crime and 0.047 for property crime. All variables were statistically significant, except for percent under 18 in the violent crime model (see table 2.4). The fixed effect of NDVI was -29.75 for violent crime and -44.40 for property crime. As NDVI was multiplied by 10, this coefficient indicates that, on average across block groups in all cities, a 0.1 increase in NDVI is associated with a decrease of 29.75 in the violent crime risk index; this equates to a 29.75% decrease in risk, and a decrease of 44.40% in the property crime risk index. Including NDVI as a random effect allowed for the relationship between NDVI and crime in block groups to be estimated for each city. The variation in the relationship across cities ranged from an estimated -158.0 to 21.7 for violent crime, and -189.3 to -9.5 for property crime. The varying slopes indicated that not all cities had a negative relationship between NDVI and violent crime in block groups, while property crime was negative in all cities. Model 2 was an improved fit over the baseline model (ΔAIC: 33168 for violent crime, 27279 for property crime; LRT: $\chi2$ (8) = 33191, $p<0.001$ for violent crime, $\chi2$ (8) = 27307, $p<0.001$ for property crime).

Model 3 included the addition of level 2 (city level) variables of per capita police, per capita GDP, and the rate of crime per 1,000 population. Pseudo R^2 increased to 0.52 from the null model for violent crime and 0.119 for property crime with the addition of level 2 variables to the model. All variables were statistically significant in the violent crime model. In the property crime model, per capita GDP was the only variable not significant. The slope coefficient for NDVI in the violent crime model increased 2.6% from -29.75 to -30.53, indicating a stronger relationship, with a 0.1 increase in NDVI associated with a decrease of 30.53 in violent crime risk. The slope coefficient for NDVI in the property crime model increased 1% from -44.40 to -44.86.

The addition of climate region in model 4 resulted in a small change in the relationship between NDVI and crime risk. For violent crime the NDVI slope increased 5% from model 3 from -30.53 to -32.07. For property crime the slope changed 2% from -44.86 to -45.77. The pseudo-R^2 increased slightly for violent crime risk to 0.548 and substantially for property crime risk to 0.31, indicating better prediction from the model. The slope variance indicated that not all cities had a negative relationship in block groups between NDVI and violent crime (95% interval -83.7 to +19.5), though with a slightly narrower range of variance than model 2. The relationship of NDVI and property crime was negatively correlated across block groups in all cities (95% interval – -88.1 to -3.5). AIC and LRT showed that model 4 was an improved fit over model 2 with only block group level variables (ΔAIC: 332.1 for violent crime, 371.0 for property crime; LRT: $\chi2$ (6) = 324.99, p<0.001 for violent crime, $\chi2$ (6) = 369.53, p<0.001 for property crime).

For the reference region – cool-dry-low – the average crime risk was 176.42 for violent crime and 105.1 for property crime. For both crime types two other climate regions differed from the cool-dry-low region, indicating that block groups in some regions do have differences in crime associated with climate. Wetter climates had higher average crime risk, with cool-wet-low and warm-wet-high regions having positive coefficients. The warm-dry-high region did not differ from the reference region. This result indicates that the mean crime risk index, when all other variables are at their average, is different based on climate region.

Table 2.4a. Model results - Violent crime risk

Violent Crime Risk

	Model 1		Model 2		Model 3		Model 4	
Predictors	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*
Intercept	**144.48** ***	5.19	**166.28** ***	5.50	**200.98** ***	3.91	**176.42** ***	6.82
NDVI			**-29.75** ***	1.87	**-30.53** ***	1.76	**-32.07** ***	1.74
Median HH income (000's)			**-0.74** ***	0.02	**-0.74** ***	0.02	**-0.73** ***	0.02
Disadvantage index			**88.72** ***	0.85	**88.39** ***	0.85	**88.40** ***	0.85
Diversity index			**-7.56** ***	0.24	**-7.51** ***	0.23	**-7.49** ***	0.23
Percent under 18			**-0.39** ***	0.05	**-0.38** ***	0.05	**-0.38** ***	0.05
Population density (log)			**-28.63** ***	0.58	**-28.78** ***	0.58	**-28.81** ***	0.58
Per capita police					**14.64** ***	3.58	4.28	3.61
Per capita GDG (000's)					**0.90** ***	0.17	**0.75** ***	0.17
Crime rate (per 1,000)					**14.52** ***	0.86	**15.49** ***	0.82
Climate (cool-wet-low)							**38.26** ***	7.33
Climate (warm-dry-high)							-18.80	9.72
Climate (warm-wet-high)							**24.28** **	7.87
Random Effects								
Residual variance	17121.64		9719.67		9727.89		9729.62	
Intercept variance	7946.91		8782.74		3060.19		2361.68	
Slope variance			845.19		732.90		691.64	
Pseudo-R^2			0.326		0.520		0.548	
AIC	752646.633		719478.611		719203.317		719146.501	

* *p<0.05* ** *p<0.01* *** *p<0.001*

Table 2.4b. Model results - Property crime risk

Property Crime Risk

	Model 1		Model 2		Model 3		Model 4	
Predictors	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*
Intercept	**133.89** ***	**2.99**	**150.51** ***	4.74	**169.85** ***	4.21	**105.11** ***	5.63
NDVI			**-44.40** ***	1.43	**-44.86** ***	1.39	**-45.77** ***	1.36
Median HH income (000's)			**-0.28** ***	0.01	**-0.27** ***	0.01	**-0.27** ***	0.01
Disadvantage index			**22.12** ***	0.52	**22.05** ***	0.52	**22.08** ***	0.52
Diversity index			**1.06** ***	0.14	**1.08** ***	0.14	**1.08** ***	0.14
Percent under 18			**-1.25** ***	0.03	**-1.25** ***	0.03	**-1.25** ***	0.03
Population density (log)			**-29.98** ***	0.35	**-30.03** ***	0.35	**-30.05** ***	0.35
Per capita police					**27.36** ***	3.30	4.21	2.60
Per capita GDG (000's)					-0.21	0.17	-0.21	0.13
Crime rate (per 1,000)					**1.83** ***	0.21	**2.44** ***	0.15
Climate (cool-wet-low)							**83.12** ***	5.85
Climate (warm-dry-high)							-2.64	7.67
Climate (warm-wet-high)							**70.07** ***	6.24
Random Effects								
Residual variance	5784.32		3604.93		3605.64		3606.03	
Intercept variance	2634.83		6615.13		3579.47		1915.53	
Slope variance			528.88		497.54		467.89	
Pseudo-R^2			0.047		0.119		0.310	
AIC	687852.946		660574.044		660416.841		660203.045	

* *p<0.05* ** *p<0.01* *** *p<0.001*

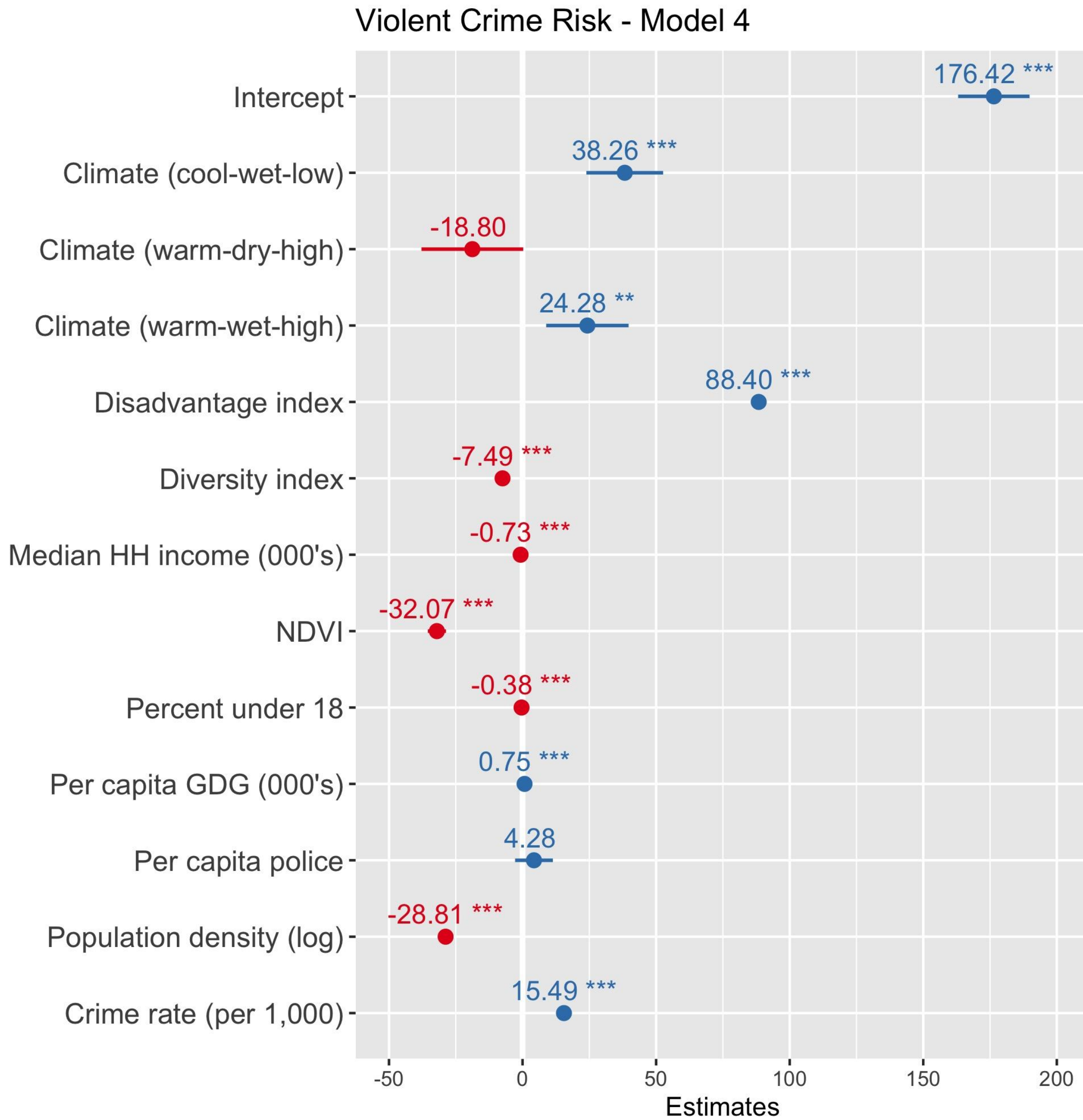

Figure 2.3a. Fixed effects for model 4, violent crime risk (estimated unstandardized coefficient and confidence interval)

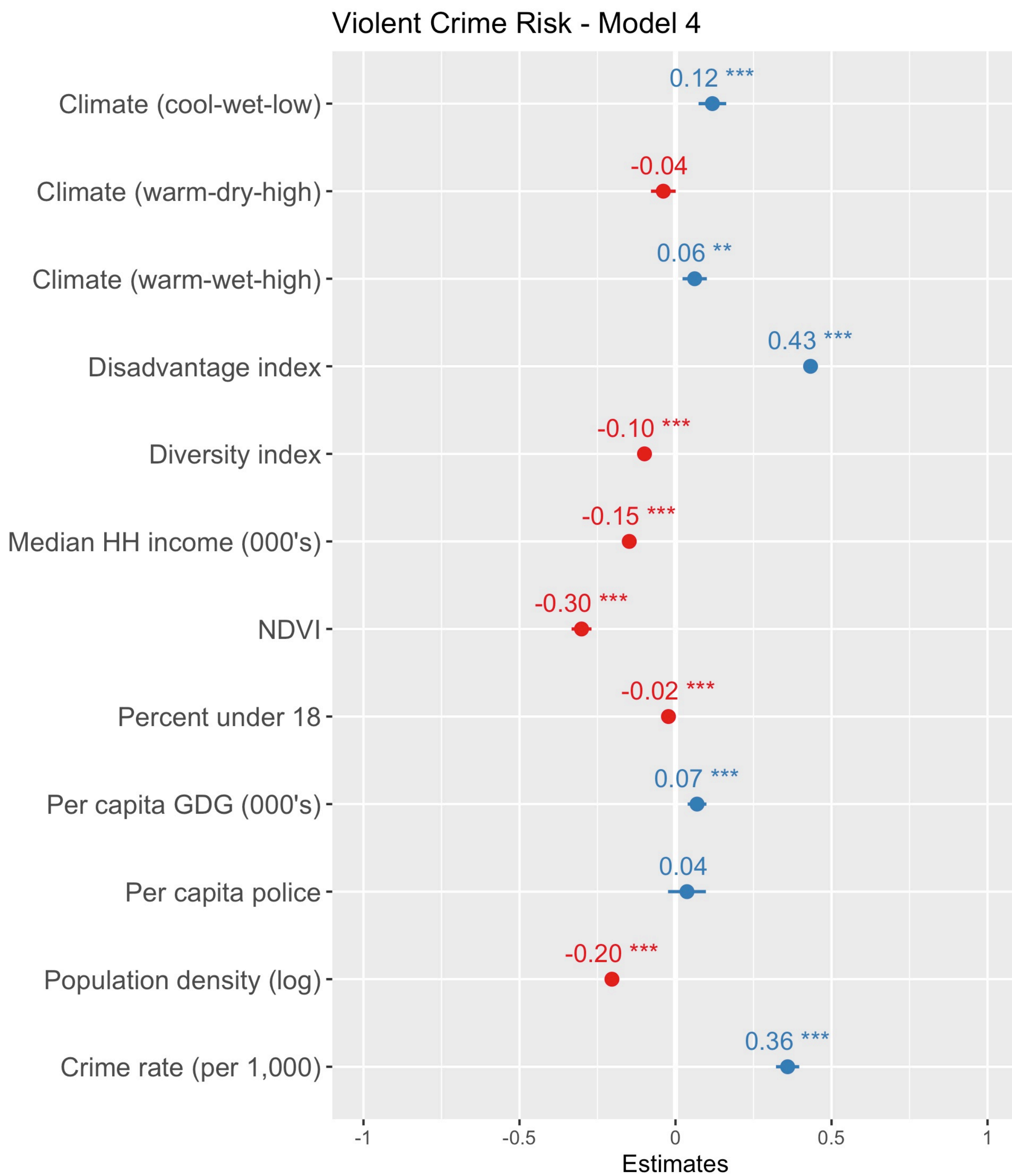

Figure 2.3b. Fixed effects for model 4, violent crime risk (estimated standardized coefficient and confidence interval)

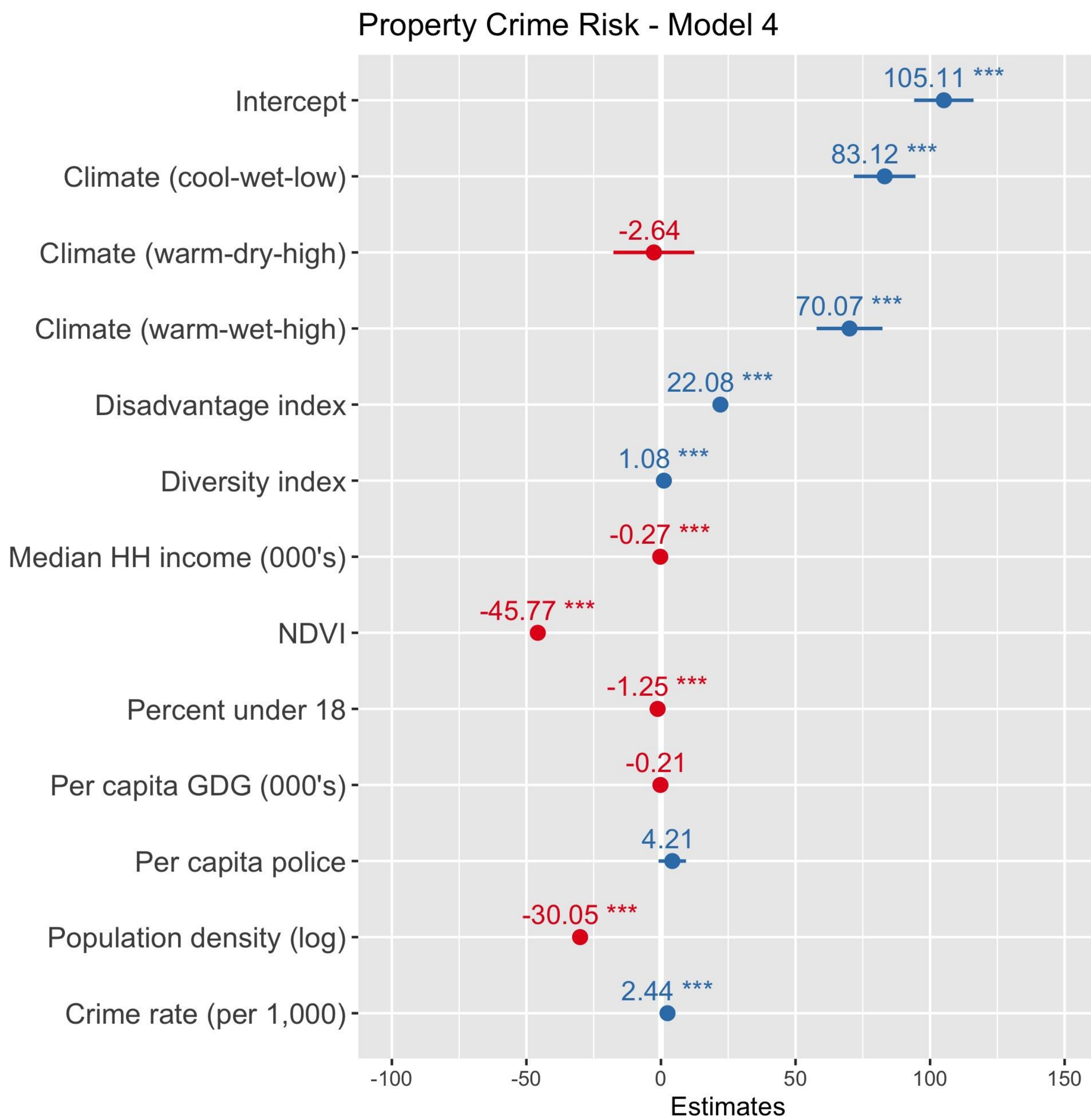

Figure 2.3c. Fixed effects for model 4, property crime risk (estimated unstandardized coefficient and confidence interval)

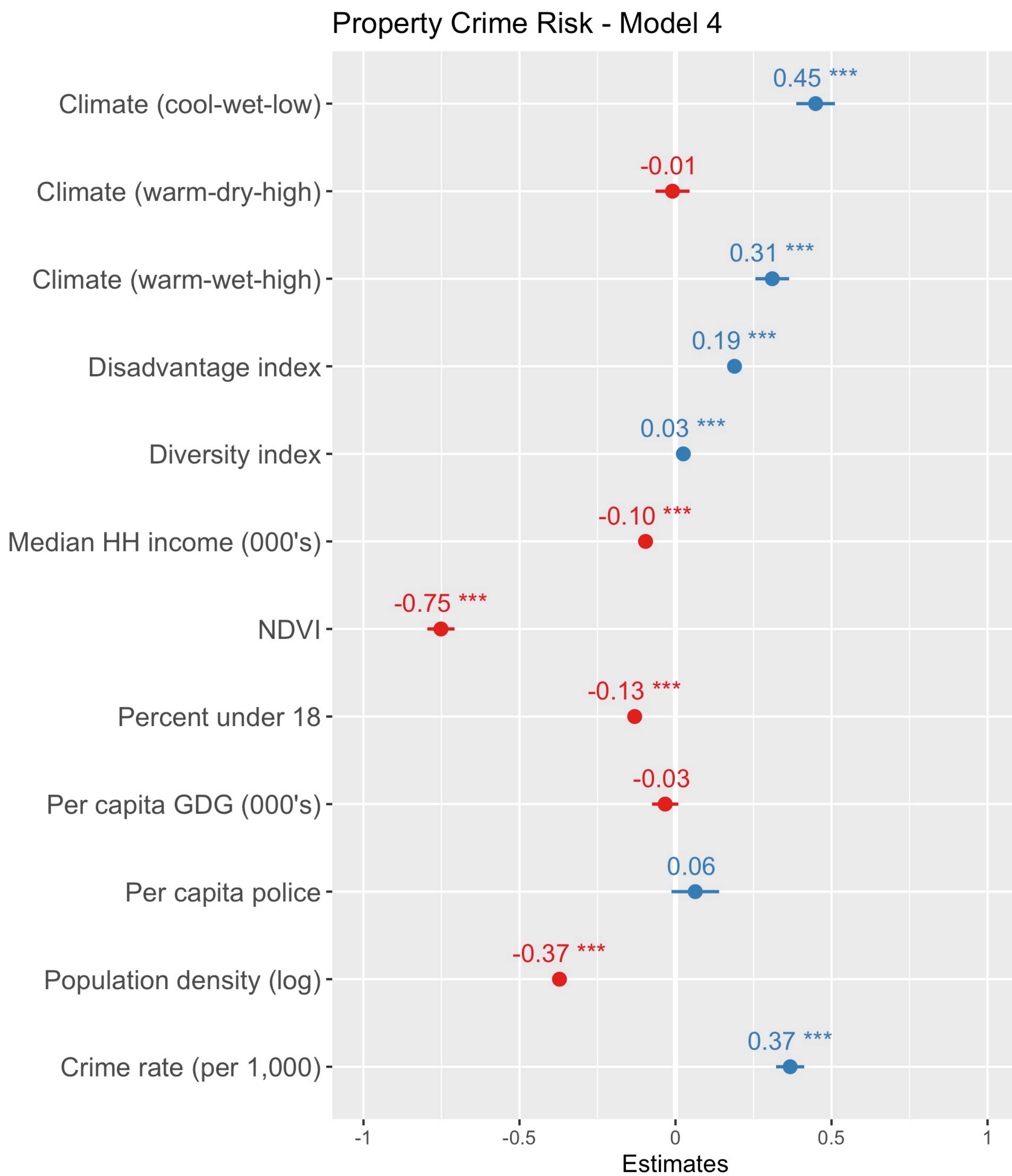

Figure 2.3d. Fixed effects for model 4, property crime risk (estimated standardized coefficient and confidence interval)

The variables with the strongest effects on crime in the final model were the disadvantage index, city crime rate, and NDVI (figures 2.3b and 2.3d). As block groups became more socially disadvantaged crime increased. Greater NDVI, as the measure of greenspace, was associated with less crime. The diversity index flipped signs between violent and property crime, indicating that greater ethnic and racial diversity was associated with less violent crime and greater property crime. The percent of the population under 18 was a weak predictor for violent crime but had a stronger association with property crime.

While the variation in the relationship between block group NDVI and crime risk was negative for property crime in all cities, violent crime showed a positive slope for some cities, indicating that greenspace was associated with increased violent crime risk in block groups for a 1% subset of cities. These cities - Chicago, IL, Detroit, MI, and Newark, NJ - had positive coefficients at a significance level of alpha=0.05 for the slope estimate (see figure 2.4)

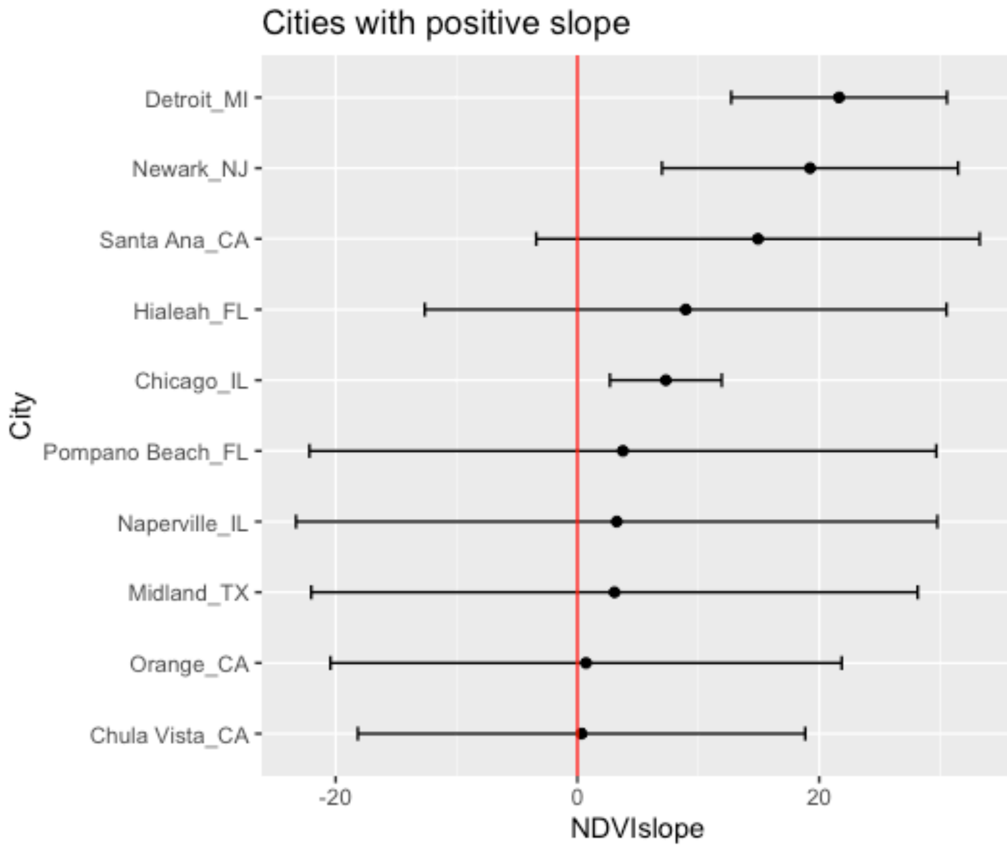

Figure 2.4. Slope estimate of NDVI and 95% error bar for cities with positive relationship between greenspace and violent crime risk

Discussion

Relationship between urban greenspace and crime

The results of our analysis suggest that, on average across all cities in the study, more greenspace in a block group is correlated with lower crime risk. This relationship held for both property and violent crime, accounting for a suite of covariates of crime. These findings align with prior research done in single cities, where vegetation was associated with less crime (Branas et al., 2018; Kuo & Sullivan, 2001b; Wolfe & Mennis, 2012), and provide new evidence that this relationship is not unique to specific cities. Our results show that this relationship persists even when including data from a large sample of cities that exhibit variation in social and geographic context.

The strongest predictors of crime risk within block groups was unsurprisingly social disadvantage. Our results confirm prior research on crime where disadvantage has been found to have more impact on violent than property crime (Krivo & Peterson, 1996). The second strongest predictor was NDVI, our measure of greenspace. Other studies, though using many different modeling strategies, have often uncovered a relationship between greenspace and crime. The results of our work show that this is true across cities and that the relationship is predominantly one of lower crime risk with more greenspace.

Higher greenspace values were related to less property and violent crime in most cities, aligning with findings from Philadelphia, PA (Wolfe & Mennis, 2012), New Haven, CT (Gilstad-Hayden et al., 2015), and Baltimore, MD (Troy et al., 2012). Many of these previous studies used differing methods, while our study has applied the same analysis to all cities in the sample. All cities in the study had a negative relationship between property crime risk and greenspace, which supports previous work on property crime and greenspace (Ye et al., 2018).

Our work does not support perspectives that view vegetation as a cause of crime through cover (Felson & Boba, 2010; Fischer & Nasar, 1992; Michael et al., 2001), though it cannot address perceptions or fear of crime that may arise from vegetation (Baran et al., 2018).

Heterogeneity across cities

Though on average more greenspace was correlated with less crime, our modeling approach also allowed us to examine the variation that exists between cities. The negative relationship, with greater greenspace being correlated with less crime risk, existed in all cities for property crime. The estimated variation in this relationship between cities ranged from -189 to -9, indicating that the impact of greenspace on property crime was not identical in all cities in the study.

For violent crime, more greenspace was correlated with less crime risk for all but 3 cities – Chicago, IL, Detroit, MI, and Newark, NJ . In these 3 cities greater block group greenspace was related to increased violent crime risk. This suggests that greenspace may have a weaker relationship with violent crime than with property crime. The three cities which had an increasing crime relationship also exhibited higher values for social disadvantage across block groups than many other cities. This positive correlation could be the result of a stronger influence of social disadvantage on crime (Wikström & Treiber, 2016), overshadowing any impact of greenspace on crime. Detroit and Newark have high values on the components of the social disadvantage variable, particularly in regard to unemployment, where Detroit was the highest and Newark was third among the study cities. Chicago had an above average value on the social disadvantage variable but does not stand out from the other cities, suggesting that other variables outside of the study may be influencing the positive correlation between violent crime and greenspace. Segregation and income inequality have been suggested as predictors of crime and could be unaccounted for variables that uniquely impact these three cities (Hipp & Kane, 2017; Krivo et al., 2009).

Chicago being one city with a positive relationship between violent crime and greenspace contradicts other findings where greenspace was associated with less violent crime (Schusler et al., 2017). This difference could be the result of differing methods, as Schusler et al. (2017) used high resolution land cover data of tree canopy only and different covariates (e.g. only poverty for an income measure). They found more tree canopy associated with less violent crime and no significant association with property crime.

Effect of climate

Including climate in studies of greenspace has been called for (Tsai et al., 2018) and climate was added as a covariate to examine if it altered the effect of greenspace on crime. When climate was included, the effect of greenspace saw little change from the identical model excluding climate, indicating that once the climate region is accounted for, greenspace still tells us something about crime. The four regions indicated differing levels of average crime, with the two dry regions having lower crime risk for both violent and property crime.

Greenspace is more intentional in arid climates, occurring where water and resources are applied to grow vegetation (Jenerette, Harlan, Stefanov, & Martin, 2011). The decision to promote vegetation in arid cities will alter how greenspace correlates with crime. The differing results in arid cities also implies that any approach to include greenspace in cities will have to be different based on the climate of the city, with more intensive strategies needed where green vegetation does not naturally occur.

Limitations

There are limitations based on the data and methods used in this study. First, the crime data is based on modeling of various data sources to estimate the amount of crime risk in each area (Pepper, Petrie, & Sullivan, 2010). This approach will contain error itself and will also contain error present in crime reporting. Second, sociodemographic data from the ACS is comprised of estimates, which in some cases may have large margins of error (Spielman, Folch, & Nagle, 2014). Lastly, this study is a cross-sectional view of the greenspace and crime relationship. Temporal trends, such as decreasing or increasing crime, were not considered. The cross-sectional approach also prevents determining any causal effect related to urban greenspace.

Future research can investigate how different types of greenspace, such as general vegetation and spaces like parks, are related to crime. Including climate region in our study provided some evidence that the greenspace and crime relationship was weaker in warmer and drier climates. These cities could be examined in greater detail to see what factors might help explain this. Lastly, greenspace was measured by NDVI in this study but humans experience greenness differently than an overhead view. More detailed measures of vegetation could be included in future studies of the relationship to investigate how the type and structure of greenspace may relate to crime.

Conclusion

Due to the variety of ecosystem services that urban greenspace provides, this type of land use is in focus as a way to improve urban well-being (Jennings, Larson, & Yun, 2016). Our study has shown that, on average, increased greenspace is associated with decreased violent and property crime. This outcome supports prior research that has examined the greenspace and crime relationship and extends the result to investigate the relationship within block groups across 301 cities in the United States.

While the amount of green vegetation is dependent on climate variables, these factors do not have a strong effect on the greenspace and crime relationship. The greenspace and crime relationship does vary across cities, illustrating that the strength of the association depends on city context. Even in light of differing city conditions, property and violent crime were found to have a negative correlation with greenspace in block groups, with only three exceptions (Chicago, IL, Detroit, MI, and Newark, NJ).

Our study reveals one association greenspace has with crime that can be beneficial in creating safer neighborhoods and areas for activity, restoration, and recreation. The possible benefit of lower crime with increased greenspace supports efforts to promote greenspace in city development, improving both the social and natural environment. For existing and future residents, greenspace can be seen as a component of increased quality-of-life for urban living.

References

Aguinis, H., Gottfredson, R. K., & Culpepper, S. A. (2013). Best-Practice Recommendations for Estimating Cross-Level Interaction Effects Using Multilevel Modeling. *Journal of Management, 39*(6), 1490–1528.

Andresen, M. A. (2015). Unemployment, GDP, and Crime: The Importance of Multiple Measurements of the Economy. *Canadian Journal of Criminology and Criminal Justice,* Vol. 57, pp. 35–58.

Baran, P. K., Tabrizian, P., Zhai, Y., Smith, J. W., & Floyd, M. F. (2018). An exploratory study of perceived safety in a neighborhood park using immersive virtual environments. *Urban Forestry & Urban Greening, 35*, 72–81.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software, 67*(1).

Beyer, K. M. M., Kaltenbach, A., Szabo, A., Bogar, S., Nieto, F. J., & Malecki, K. M. (2014). Exposure to neighborhood green space and mental health: evidence from the survey of the health of Wisconsin. *International Journal of Environmental Research and Public Health, 11*(3), 3453–3472.

Bogar, S., & Beyer, K. M. (2016). Green Space, Violence, and Crime: A Systematic Review. Trauma, *Violence & Abuse, 17*(2), 160–171.

Branas, C. C., Cheney, R. A., MacDonald, J. M., Tam, V. W., Jackson, T. D., & Ten Have, T. R. (2011). A difference-in-differences analysis of health, safety, and greening vacant urban space. *American Journal of Epidemiology, 174*(11), 1296–1306.

Branas, C. C., Rubin, D., & Guo, W. (2013). Vacant Properties and Violence in Neighborhoods. *ISRN Public Health*, 2012, 246142.

Branas, C. C., South, E., Kondo, M. C., Hohl, B. C., Bourgois, P., Wiebe, D. J., & MacDonald, J. M. (2018). Citywide cluster randomized trial to restore blighted vacant land and its effects on violence, crime, and fear. *Proceedings of the National Academy of Sciences*, *115*(12), 2946-2951.

Browning, M. H. E. M., Kuo, M., Sachdeva, S., Lee, K., & Westphal, L. (2018). Greenness and school-wide test scores are not always positively associated – A replication of "linking student performance in Massachusetts elementary schools with the 'greenness' of school surroundings using remote sensing." *Landscape and Urban Planning, 178*, 69–72.

Bursik, R. J. (1988). Social disorganization and theories of crime and delinquency: problems and prospects. *Criminology: an Interdisciplinary Journal, 26*(4), 519–552.

Cassal, K. R. (2018). *2018 Esri Diversity Index*. Esri.

Ceccato, V. (2014). The nature of rape places. *Journal of Environmental Psychology, 40*, 97–107.

Chen, Y., Li, Y., & Li, J. (2016). Investigating the influence of tree coverage on property crime: a case study in the city of Vancouver, British Columbia, Canada. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLI-B2, 695–702.

Crewe, K. (2001). Linear Parks and Urban Neighbourhoods: A Study of the Crime Impact of the Boston South-west Corridor. *Journal of Urban Design, 6*(3), 245–264.

Donovan, G. H., & Prestemon, J. P. (2010). The Effect of Trees on Crime in Portland, Oregon. *Environment and Behavior, 44*(1), 3–30.

Esri. (2016). 2016 USA Crime Index [Data set]. 2016 USA Crime Index. Retrieved from https://www.arcgis.com/home/item.html?id=b3802d8a309544b791c2304fece864dc

Federal Bureau of Investigation. (2004). *Uniform Crime Reporting Handbook*. Retrieved from U.S. Department of Justice website: https://www2.fbi.gov/ucr/handbook/ucrhandbook04.pdf

Federal Bureau of Investigation. (2016). Crime in the United States, 2015 [Data set]. Crime in the United States, 2015. Retrieved from https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015

Felson, M., & Boba, R. L. (2010). *Crime and everyday life*. Sage.

Fischer, B., & Nasar, J. (1992). The fear of crime in relation to three exterior site features. *Environment and Behavior, 24*(1).

Gascon, M., Cirach, M., Martínez, D., Dadvand, P., Valentín, A., Plasència, A., & Nieuwenhuijsen, M. J. (2016). Normalized difference vegetation index (NDVI) as a marker of surrounding greenness in epidemiological studies: The case of Barcelona city. *Urban Forestry & Urban Greening, 19*(Supplement C), 88–94.

Gilstad-Hayden, K., Wallace, L. R., Carroll-Scott, A., Meyer, S. R., Barbo, S., Murphy-Dunning, C., & Ickovics, J. R. (2015). Research note: Greater tree canopy cover is associated with lower rates of both violent and property crime in New Haven, CT. *Landscape and Urban Planning, 143*, 248–253.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*.

Grace, J. (2008). Climatic Tolerance and the Distribution of Plants. *The New Phytologist, 106*, 113–130.

Hipp, J. R., & Kane, K. (2017). Cities and the larger context: What explains changing levels of crime? *Journal of Criminal Justice, 49*, 32–44.

Hox, J. J., Moerbeek, M., & van de Schoot, R. (2010). *Multilevel Analysis: Techniques and Applications, Second Edition*. Routledge.

IPCC. (2014). Climate Change 2014: *Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. Retrieved from http://www.ipcc.ch/pdf/assessment_report/ar5/syr/SYR_AR5_FINAL_full_wcover.pdf

Jenerette, G. D., Harlan, S. L., Stefanov, W. L., & Martin, C. A. (2011). Ecosystem services and urban heat riskscape moderation: water, green spaces, and social inequality in Phoenix, USA. *Ecological Applications, 21*(7), 2637–2651.

Jennings, V., Larson, L., & Yun, J. (2016). Advancing Sustainability through Urban Green Space: Cultural Ecosystem Services, Equity, and Social Determinants of Health. *International Journal of Environmental Research and Public Health, 13*(2), 196.

Kaczynski, A. T., Potwarka, L. R., & Saelens, B. E. (2008). Association of park size, distance, and features with physical activity in neighborhood parks. *American Journal of Public Health, 98*(8), 1451–1456.

Kaplan, S. (1995). The restorative benefits of nature: Toward an integrative framework. *Journal of Environmental Psychology, 15*(3), 169–182.

Keith, S. J., Larson, L. R., Shafer, C. S., Hallo, J. C., & Fernandez, M. (2018). Greenway use and preferences in diverse urban communities: Implications for trail design and management. *Landscape and Urban Planning, 172*, 47–59.

Kimpton, A., Corcoran, J., & Wickes, R. (2017). Greenspace and Crime: An Analysis of Greenspace Types, Neighboring Composition, and the Temporal Dimensions of Crime. *The Journal of Research in Crime and Delinquency, 54*(3), 303–337.

Kondo, M. C., Han, S., Donovan, G. H., & MacDonald, J. M. (2017). The association between urban trees and crime: Evidence from the spread of the emerald ash borer in Cincinnati. *Landscape and Urban Planning, 157*, 193–199.

Kreft, H., & Jetz, W. (2007). Global patterns and determinants of vascular plant diversity. *Proceedings of the National Academy of Sciences, 104*(14), 5925–5930.

Krivo, L. J., & Peterson, R. D. (1996). Extremely Disadvantaged Neighborhoods and Urban Crime. *Social Forces; a Scientific Medium of Social Study and Interpretation, 75*(2), 619–648.

Krivo, L. J., Peterson, R. D., & Kuhl, D. C. (2009). Segregation, racial structure, and neighborhood violent crime. *American Journal of Sociology, 114*(6), 1765–1802.

Kubrin, C. E., & Weitzer, R. (2003). New Directions in Social Disorganization Theory. *The Journal of Research in Crime and Delinquency, 40*(4), 374–402.

Kuo, F. E., & Sullivan, W. C. (2001a). Aggression and violence in the inner city: Effects of environment via mental fatigue. *Environment and Behavior, 33*(4), 543–571.

Kuo, F. E., & Sullivan, W. C. (2001b). Environment and Crime in the Inner City. *Environment and Behavior, 33*(3), 343–367.

Land, K. C., McCall, P. L., & Cohen, L. (1990). Structural Covariates of Homicide Rates: Are There Any Invariances Across Time and Social Space? *The American Journal of Sociology, 95*(4), 922–963.

Levitt, S. D. (1997). Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime. *The American Economic Review, 87*(3), 270–290.

Locke, D. H., Han, S., Kondo, M. C., Murphy-Dunning, C., & Cox, M. (2017). Did community greening reduce crime? Evidence from New Haven, CT, 1996–2007. *Landscape and Urban Planning, 161*, 72–79.

Mak, B., & Jim, C. Y. (2018). Examining fear-evoking factors in urban parks in Hong Kong. *Landscape and Urban Planning, 171*, 42–56.

Mancus, G. C., & Campbell, J. (2018). Integrative Review of the Intersection of Green Space and Neighborhood Violence. *Journal of Nursing Scholarship, 50*(2), 117–125.

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., … Fuertes, E. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research, 158*, 301–317.

McDowall, D., & Loftin, C. (2009). Do US City Crime Rates Follow a National Trend? The Influence of Nationwide Conditions on Local Crime Patterns. *Journal of Quantitative Criminology, 25*(3), 307–324.

Michael, S. E., Hull, R. B., & Zahm, D. L. (2001). Environmental factors influencing auto burglary A case study. *Environment and Behavior, 33*(3), 368–388.

Nasar, J. L., Fisher, B., & Grannis, M. (1993). Proximate physical cues to fear of crime. *Landscape and Urban Planning, 26*(1), 161–178.

Nassauer, J. I. (1995). Messy Ecosystems, Orderly Frames. *Landscape Journal, 14*(2), 161–170.

Peel, M. C., Finlayson, B. L., & McMahon, T. A. (2007). Updated world map of the Koppen-Geiger climate classification. *Hydrology and Earth System Sciences, 11*, 1633–1644.

Pepper, J., Petrie, C., & Sullivan, S. (2010). *Measurement Error in Criminal Justice Data*. In A. R. Piquero & D. Weisburd (Eds.), Handbook of quantitative criminology (pp. 353–374).

PRISM climate group. (n.d.). *PRISM climate group data* [Data set]. Retrieved from http://prism.oregonstate.edu/

R Core Team. (2017). *R: A language and environment for statistical computing* (Version 3.4). Retrieved from https://www.R-project.org/

Rhew, I. C., Vander Stoep, A., Kearney, A., Smith, N. L., & Dunbar, M. D. (2011). Validation of the normalized difference vegetation index as a measure of neighborhood greenness. *Annals of Epidemiology, 21*(12), 946–952.

Sampson, N., Nassauer, J., Schulz, A., Hurd, K., Dorman, C., & Ligon, K. (2017). Landscape care of urban vacant properties and implications for health and safety: Lessons from photovoice. *Health & Place, 46*, 219–228.

Sampson, R. J., & Groves, W. B. (1989). Community Structure and Crime: Testing Social-Disorganization Theory. *The American Journal of Sociology, 94*(4), 774–802.

Sampson, R. J., Morenoff, J. D., & Gannon-Rowley, T. (2002). Assessing "Neighborhood Effects": Social Processes and New Directions in Research. *Annual Review of Sociology, 28*(1), 443–478.

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: a multilevel study of collective efficacy. *Science, 277*(5328), 918–924.

Schusler, T., Weiss, L., Treering, D., & Balderama, E. (2017). Research note: Examining the association between tree canopy, parks and crime in Chicago. *Landscape and Urban Planning, 170*, 309-313.

Simpson, E. H. (1949). Measurement of diversity. *Nature*. *163*(4148), 688.

Singer, J. D., & Willett, J. B. (2003). *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. Oxford University Press.

Spielman, S. E., Folch, D., & Nagle, N. (2014). Patterns and causes of uncertainty in the American Community Survey. *Applied Geography, 46*, 147–157.

Sreetheran, M., & van den Bosch, C. C. K. (2014). A socio-ecological exploration of fear of crime in urban green spaces – A systematic review. *Urban Forestry & Urban Greening, 13*(1), 1–18.

Stephenson, N. L. (1990). Climatic control of vegetation distribution: the role of the water balance. *The American Naturalist, 135*(5), 649–670.

Sugiyama, T., Carver, A., Koohsari, M. J., & Veitch, J. (2018). Advantages of public green spaces in enhancing population health. *Landscape and Urban Planning, 178*, 12–17.

Taylor, L., & Hochuli, D. F. (2017). Defining greenspace: Multiple uses across multiple disciplines. *Landscape and Urban Planning, 158*, 25–38.

Troy, A., & Grove, J. M. (2008). Property values, parks, and crime: A hedonic analysis in Baltimore, MD. *Landscape and Urban Planning, 87*(3), 233–245.

Troy, A., Grove, J. M., & O'Neil-Dunne, J. (2012). The relationship between tree canopy and crime rates across an urban–rural gradient in the greater Baltimore region. *Landscape and Urban Planning, 106*(3), 262–270.

Tsai, W.-L., McHale, M. R., Jennings, V., Marquet, O., Hipp, J. A., Leung, Y.-F., & Floyd, M. F. (2018). Relationships between Characteristics of Urban Green Land Cover and Mental Health in U.S. Metropolitan Areas. *International Journal of Environmental Research and Public Health, 15*(2).

U S Department of Commerce. (2015). *Measuring the Economy: A Primer on GDP and the National Income and Product Accounts*. Retrieved from U.S. Department of Commerce website: https://www.bea.gov/national/pdf/nipa_primer.pdf

Walker, K. (2018). *tidycensus: Load US Census Boundary and Attribute Data as "tidyverse" and "sf"-Ready Data Frames* (Version 0.4.6). Retrieved from https://CRAN.R-project.org/package=tidycensus

Weier, J., & Herring, D. (2000, August 30). *Measuring vegetation (NDVI & EVI)*. Retrieved from https://earthobservatory.nasa.gov/Features/MeasuringVegetation/

Wikström, P.-O. H., & Treiber, K. (2016). Social Disadvantage and Crime: A Criminological Puzzle. *The American Behavioral Scientist, 60*(10), 1232–1259.

Wolfe, M. K., & Mennis, J. (2012). Does vegetation encourage or suppress urban crime? Evidence from Philadelphia, PA. *Landscape and Urban Planning, 108*(2–4), 112–122.

Ye, C., Chen, Y., & Li, J. (2018). Investigating the Influences of Tree Coverage and Road Density on Property Crime. *ISPRS International Journal of Geo-Information, 7*(3), 101.

CHAPTER THREE

BEAT THE HEAT: CRIME REDUCTION EFFECTS OF URBAN GREENSPACE DIMINISH UNDER EXTREME HEAT CONDITIONS

Abstract

An increase in crime can be one detrimental outcome of climate change and higher temperatures in urban environments. Urban greenspace is one method that can reduce local temperatures. We sought to examine if the amount of greenspace in urban neighborhoods moderates the relationship between crime and hot weather, measured as thermal comfort (a metric that uses temperature, humidity, wind, and solar radiation to represent the human experience of hot weather). Our results, based on 301 cities in the United States, indicated that the relationship between crime and the number of hot days (days with thermal comfort over 90ºF) was dependent on the amount of greenspace in census block groups. Accounting for common covariates of crime, greener block groups had lower average crime risk and saw little change in violent crime risk with more hot days. Areas with less greenspace saw the strongest relationship between crime and hot days, having more hot days associated with less crime. Violent crime was most impacted by local greenspace, while property crime saw a small effect of greenspace. The results point to the complex interactions greenspace has with social and environmental aspects of the city. Future research could examine this relationship in greater detail with the availability of higher resolution weather and crime data.

Introduction

Cities are experiencing more frequent extremes in weather as a result of climate change, bringing about multiple challenges (IPCC, 2014). The increasing likelihood of extreme hot weather is a threat to urban residents' health and well-being (Kovats & Hajat, 2008) and can lead to increased crime and conflict (Anderson, 2001; Burke, Hsiang, & Miguel, 2015; Hsiang, Burke, & Miguel, 2013; Ranson, 2014; Rotton & Cohn, 2000b). Adding urban greenspace is one response to high urban temperatures, being found to reduce localized heat island effects (Bowler, Buyung-Ali, Knight, & Pullin, 2010; Jenerette et al., 2007) as well as crime (Branas et al., 2018; Kuo & Sullivan, 2001b; chapter 2).

Crime and weather have been linked both anecdotally and in research. Understanding how crime, temperature, and greenspace are related can increase awareness among cities and residents of the benefits and disservices greenspace may bring.

Temperature and Crime

Among the many possible causes of crime, criminological research has included analysis of the effects of weather on criminal behavior, with the pattern of increased crime in warmer months being noted in the 1840's (Harries, Stadler, & Zdorkowski, 1984; Quetelet, 1842). In the 1960's temperature was thought to be a cause of increased riots in the later part of the decade (U S Kerner Commission, 1968). These ideas supported anecdotal evidence that crime increased in hot weather (Baron & Richardson, 1994; Brunsdon, Corcoran, Higgs, & Ware, 2009).

Empirical research on the relationship between heat and aggression sought to determine if heightened aggression could be the mechanism that leads to increased crime (Cohn, 1990; Horrocks & Menclova, 2011). By manipulating temperature, laboratory studies found that in warmer conditions aggressive behavior increased. When temperatures were manipulated over 90ºF aggression was then found to decline (Anderson, 2001; Baron & Bell, 1975; Bell & Baron, 1977). This result suggested that at high temperatures participants were more concerned with escaping the heat than acting out aggression. Rather than a linear relationship, where aggression keeps increasing with temperature, the laboratory experiments point to a curvilinear relationship, with an increase in aggression until 92º-95ºF then a decrease beyond these temperatures (Baron & Bell, 1975; Bell, 1992). This curvilinear trend is called the *negative affect escape model* (Anderson, 1989).

Research outside of the laboratory has focused on studies of crime and weather data, often taken from archival sources. In all studies, crime is seen to increase as temperatures increase. Depending on methods of analysis, the pattern has shown both a linear trend (Anderson & Anderson, 1984; Anderson, Bushman, & Groom, 1997; Carlsmith & Anderson, 1979; Cotton, 1986) and a curvilinear trend (Bell & Fusco, 1986; Rotton & Cohn, 2000a) in the temperature and crime relationship (figure 2.1). Some debate remains based on variation in findings, but both laboratory and field research suggest that extreme high temperatures may work to depress crime and criminal behavior.

Additional research on longer term climate impacts on crime have predicted an increase in crime as temperatures rise (Hsiang et al., 2013; Mares, 2013; Ranson, 2014). While monthly or yearly trends do not allow specific analysis of weather impacts, the effects of reduced crime with extreme temperatures have been noticed, supporting a non-linear relationship between temperature and crime (Mares & Moffett, 2019).

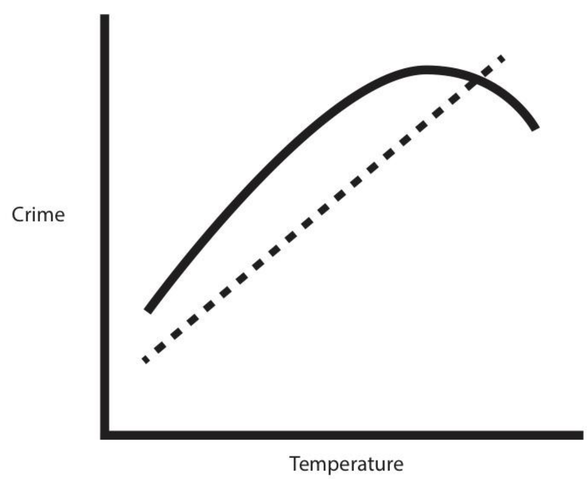

Figure 3.1. Linear and curvilinear perspective of temperature and crime relationship (Illustration by author).

If the negative affect escape model points to a crime decrease at high temperature, knowing the temperature where the inflection occurs could contribute to our understanding of crime. An exact threshold is difficult to identify, but in studies the inflection is found to occur anywhere from 85-86ºF (Mavroudeas et al., 2018; Rotton & Cohn, 2000a) to 90-92ºF (Baron, 1972; Gamble & Hess, 2012).

The concept of people seeking relief at high temperatures bears out in other research on outdoor activity, park visitation, and tourism demand (Fisichelli, Schuurman, Monahan, & Ziesler, 2015; Graff Zivin & Neidell, 2014; Rosselló-Nadal, 2014). In these studies, a decrease in activity is found at extreme high temperatures, suggesting that people are finding relief elsewhere from the discomfort of hot weather.

Regardless of the pattern of association, it is believed that a relationship exists between increased temperatures and increased crime (Bell, 2005). With episodes of high heat predicted to increase in the future, the crime and temperature relationship contributes an additional detrimental outcome of changing climate (IPCC, 2014; Ranson, 2014).

Greenspace and Crime

Greenspace encompasses all vegetated areas of a city (Taylor & Hochuli, 2017) and is found by researchers to be both a generator and a deterrent of crime. As a cause of crime, greenspace can provide cover and concealment for criminals (Felson & Boba, 2010; Mak & Jim, 2018; Michael, Hull, & Zahm, 2001). Vegetation can also limit visibility of greenspace users, which can lead to greater vulnerability to crime and lessen perceived safety of residents (Baran, Tabrizian, Zhai, Smith, & Floyd, 2018; Nasar, Fisher, & Grannis, 1993). Uncared for greenspace can also communicate a lack of oversight and attract criminal activities (Nassauer, 1995; Sampson et al., 2017).

Other research has found that greenspace contributes to a reduction in crime (see chapter 2). This outcome is thought to stem from the effect of greenspace to provide restoration (Kaplan, 1995), reduce mental fatigue (Kuo & Sullivan, 2001a; Tsai et al., 2018), and increase social cohesion (Holtan, Dieterlen, & Sullivan, 2014; Maas et al., 2009). In Chicago, IL, public housing with more vegetation was associated with fewer crime incidents (Kuo & Sullivan, 2001b). Other research in Chicago also found lower crime rates in areas with more trees (Schusler, Weiss, Treering, & Balderama, 2017). Other work connecting greenspace to crime reduction has examined street trees (Donovan & Prestemon, 2010; Kondo, Han, Donovan, & MacDonald, 2017), vacant lots (Branas et al., 2011), and tree canopy (Gilstad-Hayden et al., 2015; Schusler et al., 2017; Troy, Grove, & O'Neil-Dunne, 2012). In these studies, greater vegetation tends to correlate with decreases in crime. Only one study, in New Haven, CT, found no statistically significant difference in crime before and after a community greening program (Locke, Han, Kondo, Murphy-Dunning, & Cox, 2017).

The existing research depicts a complex relationship between greenspace and crime. Studies generally point to benefits flowing from greenspace in the form of reduced crime, though the mechanisms remain unclear. As greenspace is promoted based on the multiple benefits it provides to urban residents (including, potentially, crime reduction), it is important to better understand how greenspace interacts with other environmental conditions to influence those social benefits.

Greenspace and Temperature

Urban heat islands (UHI) are a phenomenon where cities become warmer than the surrounding areas due to their increased amount of pavement and buildings, features that absorb thermal energy and raise temperatures (Wong, Akbari, Bell, & Cole, 2011). These UHI effects are threats to human health through the impact they have vulnerable populations, especially the young and elderly (McGregor, Bessemoulin, Ebi, & Menne, 2015; McGregor & Vanos, 2018; Meehl & Tebaldi, 2004). Those concerns escalate as climate change is anticipated to increase extreme heating events, particularly in urban areas (Hajat, O'Connor, & Kosatsky, 2010).

Greenspace can be one response to increased heat by lowering local temperatures through mechanisms such as shading and evapotranspiration (Bowler et al., 2010) and by aiding in air movement within local settings. When composed of trees, greenspace is found to reduce temperatures and also provide benefit through shade (Brown, Vanos, Kenny, & Lenzholzer, 2015). This phenomenon is called the 'park cool island' effect and moderates local extremes in temperature, both during the day and at night (Chow, Pope, Martin, & Brazel, 2011; Declet-Barreto, Brazel, Martin, Chow, & Harlan, 2013). The effect of urban greenspace on temperatures could play a role in the relationship between thermal conditions and crime, with greenspace influencing temperature, humidity, wind, and sun to create a more comfortable thermal environment (Armson, Stringer, & Ennos, 2012; Bowler et al., 2010).

Thermal comfort

Temperature is the primary weather variable that humans sense, but it does not capture the full measure of the weather that is experienced. Key to understanding how environmental conditions are felt is the concept of thermal comfort, a term that represents a combination of weather variables that make up the sensation of the thermal environment (Parsons, 2014). While straightforward, this definition captures that aspect of the environment which influences human behavior through how comfortable a person feels with regard to the weather. Only when a person becomes uncomfortably cold or hot do they begin to seek out how to get back to a comfortable situation.

Thermal comfort is made up of four basic variables: air temperature, humidity, air movement, and radiant temperature (Parsons, 2014). The full complement of these variables act on humans in outdoor situations and should be taken into account when assessing how the environment impacts behavior (McGregor & Vanos, 2018; Verbos, Altschuler, & Brownlee, 2017).

It is important to differentiate between climate and weather in regards to crime. Weather is the atmospheric conditions of a particular setting at a certain time. These are the environmental conditions that humans encounter in daily life. Climate is the longer term aggregation of weather, typically over 30 years (de Freitas, 2003). The temporal scale of human actions that lead to crime is short, so weather is the more relevant environmental condition to be examined. It is the variables of weather that form the inputs for thermal comfort.

Numerous thermal comfort indices have been proposed over the last 100 years (Epstein & Moran, 2006). A more recent addition is the Universal Thermal Comfort Index (UTCI), developed in the early 2000's (Jendritzky, Maarouf, & Staiger, 2001). The UTCI seeks to incorporate an improved model of how humans experience weather conditions, taking into account clothing and the heat balance between a person and their immediate environment. Using measures of air temperature, relative humidity, wind, and solar radiation, a temperature value can be calculated that represents the thermal conditions being experienced. The resulting temperatures can be categorized according to the cold or heat stress that a person would experience (Błażejczyk et al., 2013).

Despite its recent introduction, the UTCI has been used in studies across various climates and in comparison to existing thermal indices. The results are found to be useful for many applications that attempt to understand human response to thermal environments, particularly for studying thermal conditions of open space (Bröde et al., 2012) and in assessing heat-related health risks (Di Napoli, Pappenberger, & Cloke, 2018). The UTCI is used by researchers in the fields of urban design (Reinhart, Dhariwal, & Gero, 2017), tourism (Rutty & Scott, 2015), and public health (Di Napoli et al., 2018; McGregor & Vanos, 2018), but have seen little application to studies of crime.

While previous research links higher temperatures with increased crime, greenspace with decreased crime, and greenspace with decreased temperatures, no work has explored the interrelationship that might exist between these phenomena. To address this gap we examined the following research question - Does greenspace, defined by remotely sensed vegetative cover (Markevych et al., 2017; Pearsall & Christman, 2012; Wolfe & Mennis, 2012), moderate the relationship between temperature, measured by thermal comfort, and crime risk in census block groups? If so, how and in what direction?

Methods

To investigate how greenspace may moderate the relationship between crime and thermal comfort, data were collected for census block groups in 301 cities in the U.S. with populations over 100,000 (see Appendix A). The unit of analysis was census block groups, with block groups greater than 50% within city boundaries selected, as census and administrative boundaries do not match exactly. This resulted in a sample of 62,068 block groups in 301 cities.

Dependent Variable

Crime Data - A crime risk index was used to assess violent and property crime in block groups (Esri, 2015). This index represents the crime risk in an area, and is derived from data reported by law enforcement agencies and statistical models to determine crime risk at the block group level. The index is based on 100 being the national average and a one-unit change being a percent change in risk (i.e. 120 equals a 20% increase in risk from the national average) (Esri, 2015). The data are provided that align with the Federal Bureau of Investigation (FBI) Uniform Crime Report (UCR) Part 1 crimes, covering violent and property crimes (Federal Bureau of Investigation, 2004).

Level 1 - census block groups

Greenspace measure - Greenspace was operationalized as the measure of vegetation, assessed through the normalized difference vegetation index (NDVI). This calculated measure is widely used in the study of public health, crime, and environmental behavior, where greenspace is viewed as all remotely sensed vegetation (Markevych et al., 2017; Wolfe & Mennis, 2012; Younan et al., 2016). NDVI is a unitless measure ranging from -1 to 1, with an approximate translation of values to equal bare soil, water, or impervious surfaces below 0.1, grasses and shrubs from 0.2 to 0.5, and dense vegetation and forest above 0.6 (Weier & Herring, 2000). For this study, NDVI is multiplied by 10 to aid in the interpretation of model results. The input imagery was from the Landsat 8 satellite for 2015 processed within the Google Earth Engine platform (Gorelick et al., 2017).

Sociodemographic data - Social covariates of crime were sourced from the 2011 - 2015 5-year American Community Survey (ACS). Variables used at the block group level include 1) median household income, 2) percent under 18 years old, 3) population density, 4) percent housing vacant, and 5) percent housing renter occupied.

Two indices were generated to capture local social disadvantage and ethnic/racial diversity within block groups. The disadvantage index is the averaged z-scores of four variables: 1) percent unemployed, 2) percent with less than a high school diploma, 3) percent of households that are female headed, and 4) percent of families below poverty (Krivo, Peterson, & Kuhl, 2009; Sampson, Raudenbush, & Earls, 1997). The diversity index is a measure of ethnic or racial diversity in a block group using demographic variables of race and hispanic origin. This is calculated using Simpson' Index for the 14 population categories provided in the ACS data (Cassal, 2018; Simpson, 1949). Simpson's index represents the probability of two randomly selected individuals being from the same group and ranges from 0 (homogeneous) to 1 (heterogeneous).

Level 2 - cities

Weather data - Weather inputs used to calculate the UTCI were sourced from the North American Land Data Assimilation System (NLDAS-2)(NASA/GSFC, 2013) which provides hourly estimates of weather variables based on observed measures and modeled data. The hourly data were used to obtain the weather variables at the time of maximum temperature for each day in 2015 for all block groups in the study to capture the hottest thermal condition a person might encounter during the day. These variables — air temperature, relative humidity, wind speed, and solar radiation — were used to calculate the UTCI based on the equation provided by the International Society of Biometeorology Commission (Bröde, 2009; Bröde et al., 2012) in R Statistical Software (R Core Team, 2017).

UTCI values were categorized into thermal stress levels according to Błażejczyk et al (2010) (see table 3.1), then aggregated to a measure of the number of days in each category for each city. To capture the total number of days that were in high heat stress, the categories of strong, very strong, and extreme heat stress were combined. The combined number of days in heat stress is represented as "hot days" and reflects the number of days in 2015 in each city where the UTCI was greater than 90ºF.

Table 3.1. Universal thermal comfort index ranges for thermal stress

UTCI (°C) range	**ºF**	**Stress Category**
above 46	above 114.8	extreme heat stress
38 to 46	100.4 to 114.8	very strong heat stress
32 to 38	89.6 to 100.4	strong heat stress
26 to 32	78.8 to 89.6	moderate heat stress
9 to 26	48.2 to 78.8	no thermal stress
9 to 0	32 to 48.2	slight cold stress
0 to -13	32 to 8.6	moderate cold stress
-13 to -27	8.6 to -16.6	strong cold stress
-27 to -40	-16.6 to -40	very strong cold stress
below -40	below -40	extreme cold stress

Błażejczyk et al., 2013

Crime. Crime data was collected at the city level from the FBI UCR to provide a measure of crime in each city context, which serves as a large-scale view of crime in each city that could explain local crime risk (McDowall & Loftin, 2009). Counts of the number of offenses and population were obtained for all cities (Federal Bureau of Investigation, 2016). Using these counts, a rate per 1,000 persons was calculated for 2015 for violent and property crimes.

Police force. The size of city police forces is found to the associated with crime in prior research (Levitt, 1997). For this reason, the size of the municipal law enforcement agency was used as a measure of the level of policing that exists in a city. The number of officers was obtained from FBI law enforcement employment data for 2015 and divided by city population (Federal Bureau of Investigation, 2016). This police force variable is the number of officers per 1,000 persons. Some cities were found to contract out law enforcement to county agencies. In such cases, the police force rate for the area served by a county law enforcement agency was used for the city.

GDP. The economic condition of a city is one contextual variable that is thought to contribute to crime (Andresen, 2015). To account for differences in the economic context of cities, the per capita metropolitan gross domestic product (GDP) was obtained from the Bureau of Economic Analysis. GDP is calculated for metropolitan regions and provides a measure of "the value of the goods and services produced" within an area (U S Department of Commerce, 2015).

Select variables were rescaled to aid in interpretation. As stated above, NDVI was multiplied by 10 so that 1 unit corresponded to 0.1 change. The same approach was used with diversity index multiplying the range from 0 to 1 to result in a range of 0 to 10. Per capita GDP, median household income, and population density were divided by 1,000.

City populations were divided by 100,000. All rescaling converted variables into similar ranges to facilitate modeling.

All variables were grand mean centered so that a value of 0 indicates the average across all block groups in the study. The dependent variable used in the analysis was the crime risk index in block groups. The independent variables at level 1 (block groups) were 1) median household income, 2) disadvantage index, 3) racial/ethnic diversity Index, 4) percent under 18, 5) population density, 6) percent housing vacant, 7) percent housing renter occupied, 8) mean NDVI. Independent variable at level 2 (cities) were: 1) crime rate per 1,000 population, 2) police officers per 1,000 population, 3) per capita GDP, and 4) hot days - number of days with UTCI greater than 90ºF. Description and sources for the variables are presented in table 3.2.

Table 3.2. Data description and sources

Variable	Description	Source
NDVI (greenspace)	Mean value of 30m pixels in block group	Landsat 8
Median Household Income	In 1,000's dollars	ACS
Percent under 18	Percent of population under 18	ACS
Population density	Number of residents per square kilometer	ACS
Disadvantage Index	Measure of social disadvantage in block group	ACS
Percent unemployed	Percent of population over 16 unemployed	ACS
Percent less than a high school	Percent of population over 25 with less than a high school diploma	ACS
Percent female headed	Percent of households that are female headed	ACS
Percent families below poverty	Percent of families below poverty	ACS
Diversity Index	Index of racial diversity in block group	ACS
Crime Risk Index	Crime rate indexed relative to national average	Esri
Crime Rate	Number of crimes per 1,000 population	FBI
Police Force	Number of officers per 1,000 population	FBI
Climate Region	Classified climate region	PRISM
GDP	Per capita GDP for Metropolitan Statistical Area, in 1,000's dollars	BEA
Hot days - UTCI > 90ºF	NLDAS-2 hourly weather variables	NASA

ACS - American Community Survey 2011-2015 5-year Estimates
Esri, Inc. - Demographics 2016
FBI - Federal Bureau of Investigation, Crime in the United States 2015
PRISM - PRISM Climate Group (http://www.prism.oregonstate.edu/)
BEA - Bureau of Economic Analysis (https://www.bea.gov/data/gdp/gdp-metropolitan-area)
NASA - North American Land Data Assimilation System

Analysis

To examine the associations between crime risk, hot days, greenspace, and covariates, a bivariate analysis was conducted. Significance of correlations were tested by Pearson product at *alpha* = 0.05.

A multilevel modeling approach was used to account for the similarity that may exist between block groups within the same city, which would violate the assumption of independence in ordinary least squares regression (Snijders & Bosker, 2012). Models were constructed from simple to more complex as suggested by Hox (2010). The initial intercept-only null model, model 1, allowed for the determination of variability attributable to cities. Model 2 added level one, or block group, variables. Model 3 added level two, or city level, variables. The final model added the interaction of hot days and NDVI. All models were compared using Akaike's Information Criterion (AIC) and likelihood ratio tests to examine if the added variables improved model fit. As a measure of "explained" variance the overall pseudo-R^2 was calculated by squaring the correlation between predicted and observed values for the response variable (block group crime risk index) in each model (Aguinis, Gottfredson, & Culpepper, 2013; Singer & Willett, 2003).

Linear multilevel models were fit in R statistical software (version 3.5) using the *lme4* package (Bates, Mächler, Bolker, & Walker, 2015). The Crime Risk Index response was included as the dependent variable and fixed effects were added for covariates, NDVI, hot days, and the interaction between NDVI and hot days. City was included as a random effect to allow for intercepts to vary across the cities. The final model specification and moderation relationship are as follows:

Model 1: Crime Index ~ α + (1|City)

Model 2: *Model 1* + Median Income + % Renter + % Vacant + Population Density + Disadvantage + Diversity + % under 18 + NDVI

Model 3: *Model 2* + Per capita GDP + Per capita Police + Hot days + City crime rate

Model 4: *Model 3* + (NDVI × Hot Days)

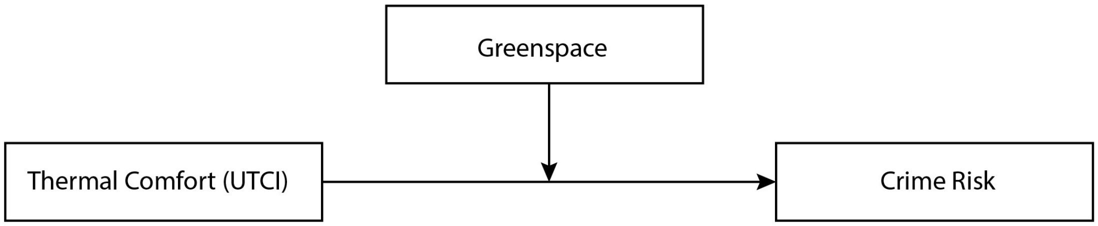

Figure 3.2. Conceptual diagram of greenspace moderation on thermal comfort and crime risk

Results

Descriptive statistics

Descriptive statistics for the level 1 (block groups) and level 2 (cities) variables are given in table 3.2. The city mean of the block group violent crime index varied from 12.5 in Irvine, CA to 525 in Detroit, MI. The block group property crime index varied from 34.7 in Irvine, CA to 327 in Spokane, WA. Hot days ranged from 3 to 236 (Daly City, CA; Oxnard, CA) across all cities in the study.

Table 3.3. Descriptive statistics of level 1 and level 2 variables

Level	Variable	mean	sd	min	max
Level 1 - Census Block Group					
	Crime Risk Property	136	92.3	3	1,030
	Crime Risk Violent	180	162	2	1,334
	Disadvantage Index	0.05	0.791	-1.19	4.28
	Diversity Index	4.76	2.14	0	8.79
	Median Household Income (000's)	55.7	32.9	2.5	250
	Mean NDVI	4.07	1.52	0.514	8.06
	Percent Under 18	22.3	9.7	0	69.7
	Percent Renter	49.27	9.97	0	92.94
	Percent Vacant	10.25	27.66	0	100
	Area (square kilometer)	1.05	3.47	0	223
	Total Population	1,444	846	23	22,054
	Population Density per Square Kilometer	5,610	9,882	4.18	220,955
Level 2 - City					
	Per Capita GDG (000's)	56.6	14.9	20.5	178
	Per Capita Police (per 1,000)	2.52	1.39	0.09	5.86
	Crime Rate - Property (per 1,000)	34.4	13.9	9.95	93.3
	Crime Rate - Violent (per 1,000)	6.91	3.75	0.51	18.2
	Total Population	1,530,178.87	2,483,657.21	98,312	8,550,405
	Population Density per Square Kilometer	7,243.68	7,762.06	615.86	28,363
	Number of Block Groups	198.16	408.47	28.00	5,858
	Hot days	106.40	55.16	3.00	236

Bivariate analysis

Pearson product moment correlations between the crime risk index, hot days, greenspace, and covariates showed significant associations at alpha = 0.05 level. The strongest correlations existed between median income, percent renter, violent crime risk, and disadvantage. The number of hot days was negatively correlated with violent and property crime risk, though weakly. The greater the number of hot days the lower NDVI, violent, and property crime were in the data. Correlations that were not significant were median income with NDVI and population density, population and per capita GDP, percent under 18 and violent crime rate.

The relationship between crime and thermal comfort is predicted to be non-linear based on the negative affect escape model (Bell & Baron, 1977). Despite only focusing on the high temperature region of the relationship, linearity between crime risk and hot days was checked. Non-linear association did not provide improved fit over linear assumptions so the model was fit with a linear multilevel approach.

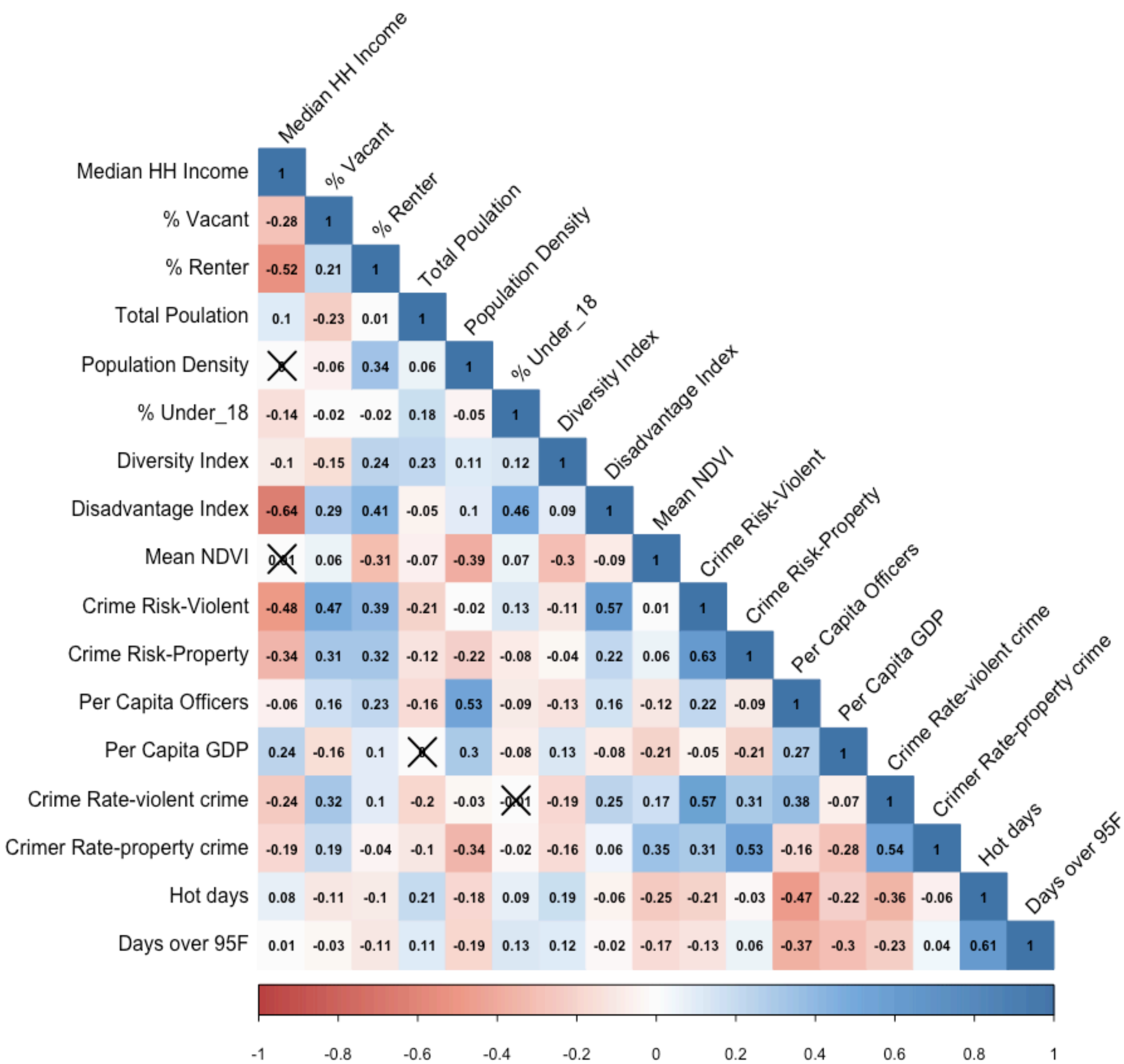

Figure 3.3. Correlation matrix. X cells indicate p > 0.05.

Model results

The initial null model, model 1, was fit for violent and property crime. The results served as the baseline for further model development and for observing changes in variance as more variables are added. The variance measures of the null model provide for the calculation of the intraclass correlation for both crime types, which provides a measure of the variation in the block groups that is attributable to cities and an indication if a multilevel modeling approach is appropriate. Intraclass correlation (ICC) for violent crime was 0.316 and property crime was 0.313. These indicate that 31.6% of the variation in violent crime and 31.3% of property crime is at the level of cities, supporting the use of a multilevel modeling approach.

Model 2 adds the level 1, or block group level, variables. The pseudo R^2 was 0.452 for violent crime and 0.080 for property crime. All block group level variables were significant (see table 3.3), with NDVI also negative (-14.78 in violent crime, -24.91 in property crime). The coefficients indicate that a 0.1 increase in NDVI is associated with a decrease in the crime risk index of 14.78 and 24.91. A likelihood ratio test (LRT) was carried out to examine model improvement between model 1 and 2. The result showed an improved fit by model 2 (Violent: ΔAIC- 36600, $\chi^2(8)$=36641, p= < 0.001/Property: ΔAIC- 23273, $\chi^2(8)$=23231, p= < 0.001).

Model 3 added the level 2, or city level, variables. Approximation of the variance explained increased from the previous model with only block group level variables, with a pseudo R^2 of 0.601 for violent crime and 0.372 for property crime. With the addition of city variables, the coefficient for hot days in the violent crime model was negative at -0.19, so that one additional day with UTCI above 90ºF was associated with a decrease of 0.19 in the crime risk index. For property crime the hot days variable was significant and negative at -0.26. NDVI remained negatively associated with violent and property crime (2% change for violent crime and 1% change for property crime). Model 3 had better fit over model 2 based on the result of the LRT (violent crime: $\chi^2(4)$=422.03, p= < 0.001/property crime: $\chi^2(4)$ =336.28, p= < 0.001). Without the interaction of NDVI and hot days each variable had an inverse relationship with crime.

The interaction of NDVI and hot days addresses the question of how greenspace moderates the crime and thermal comfort relationship, with model 4 adding the interaction term between hot days and NDVI. This final model accounted for a small increase in the pseudo R^2 from model 3 (violent crime: 0.605, property crime: 0.380). The interaction term was significant with a coefficient of 0.10 for violent crime and 0.03 for property crime, indicating that an increase in NDVI was associated with a weakening in the relationship between crime and hot days (figure 3.3). In the violent crime model the interaction indicates that a greater amount of greenspace weakens the relationship between hot days and crime. At one standard deviation above the mean NDVI value the relationship approaches 0, or no change as there are more hots days. For property crime, the coefficient for hot days remained significant at -0.26 when NDVI is at the mean. The interaction indicates that above average NDVI will result in the slope for hot days weakening by a small amount for property crime risk. The model with the interaction was a better fit over model 3 based on the LRT (violent crime: $\chi^2(1)$=107.97, p= < 0.001, property crime: $\chi^2(1)$=21.86, p= < 0.001).

Table 3.4a. Model results for violent crime risk

	Model 1		Model 2		Model 3		Model 4	
Predictors	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*
Intercept	**144.48** ***	5.19	**157.88** ***	3.96	**181.59** ***	2.59	**182.49** ***	2.47
Population Density			**-2.17** ***	0.06	**-2.17** ***	0.06	**-2.21** ***	0.06
Median Household Income			**-0.20** ***	0.02	**-0.19** ***	0.02	**-0.20** ***	0.02
Disadvantage Index			**76.93** ***	0.84	**76.51** ***	0.83	**76.48** ***	0.83
Diversity Index			**-8.74** ***	0.23	**-8.67** ***	0.23	**-8.76** ***	0.23
Percent Renter			**1.10** ***	0.02	**1.10** ***	0.02	**1.11** ***	0.02
Percent Vacant			**3.21** ***	0.05	**3.20** ***	0.05	**3.20** ***	0.05
NDVI			**-14.78** ***	0.53	**-14.48** ***	0.52	**-13.00** ***	0.53
Percent under 18			-0.09	0.05	-0.08	0.05	-0.07	0.05
Hot Days					**-0.19** ***	0.04	**-0.17** ***	0.04
Per capita GDP (000's)					**0.56** ***	0.12	**0.58** ***	0.12
Per capita Police					**-6.85** *	2.83	**-9.83** ***	2.71
Crime Rate (per 1,000)					**16.44** ***	0.68	**16.66** ***	0.65
Hot days X NDVI							**0.10** ***	0.01
Random Effects								
Residual variance	17121.64		9266.53		9266.91		9254.77	
Intercept variance	7946.91		4609.92		1070.67		963.67	
Pseudo-R^2	-		0.452		0.601		0.605	
AIC	752646.633		716046.513		715636.741		715538.817	

* p<0.05   ** p<0.01   *** p<0.001

Table 3.4b. Model results for property crime risk

	Model 1		Model 2		Model 3		Model 4	
Predictors	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*	*Estimates*	*std. Error*
Intercept	**133.89** ***	2.99	**141.97** ***	3.70	**145.40** ***	2.87	**145.66** ***	2.79
Population Density			**-1.83** ***	0.04	**-1.82** ***	0.04	**-1.84** ***	0.04
Median Household Income			**0.19** ***	0.01	**0.19** ***	0.01	**0.18** ***	0.01
Disadvantage Index			**16.45** ***	0.54	**16.35** ***	0.54	**16.33** ***	0.54
Diversity Index			**-0.48** **	0.15	**-0.47** **	0.15	**-0.50** ***	0.15
Percent Renter			**1.00** ***	0.01	**1.00** ***	0.01	**1.00** ***	0.01
Percent Vacant			**0.92** ***	0.03	**0.92** ***	0.03	**0.92** ***	0.03
NDVI			**-24.91** ***	0.35	**-24.65** ***	0.34	**-24.13** ***	0.36
Percent under 18			**-1.28** ***	0.03	**-1.27** ***	0.03	**-1.27** ***	0.03
Hot Days					**-0.26** ***	0.04	**-0.26** ***	0.04
Per capita GDP (000's)					**-0.56** ***	0.13	**-0.56** ***	0.13
Per capita Police					1.18	2.80	0.45	2.72
Crime Rate (per 1,000)					**3.23** ***	0.17	**3.22** ***	0.17
Hot days X NDVI							**0.03** ***	0.01
Random Effects								
Residual variance	5784.32		3898.31		3898.48		3898.18	
Intercept variance	2634.83		4075.13		1313.04		1241.91	
Pseudo-R^2	-		0.079		0.372		0.380	
AIC	687852.946		664579.055		664256.990		664245.732	

* *p<0.05* ** *p<0.01* *** *p<0.001*

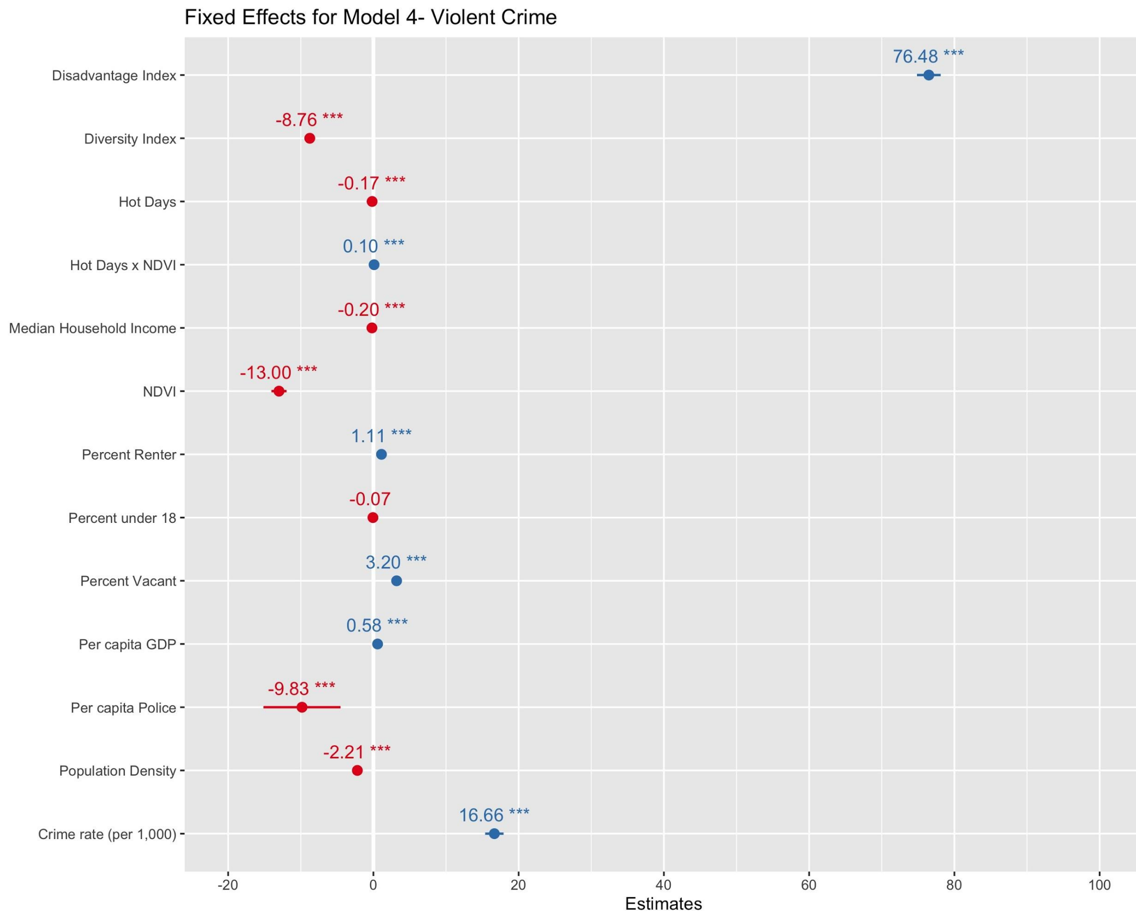

Figure 3.4a. Estimated fixed effects for violent crime risk, model 4 (unstandardized coefficients).

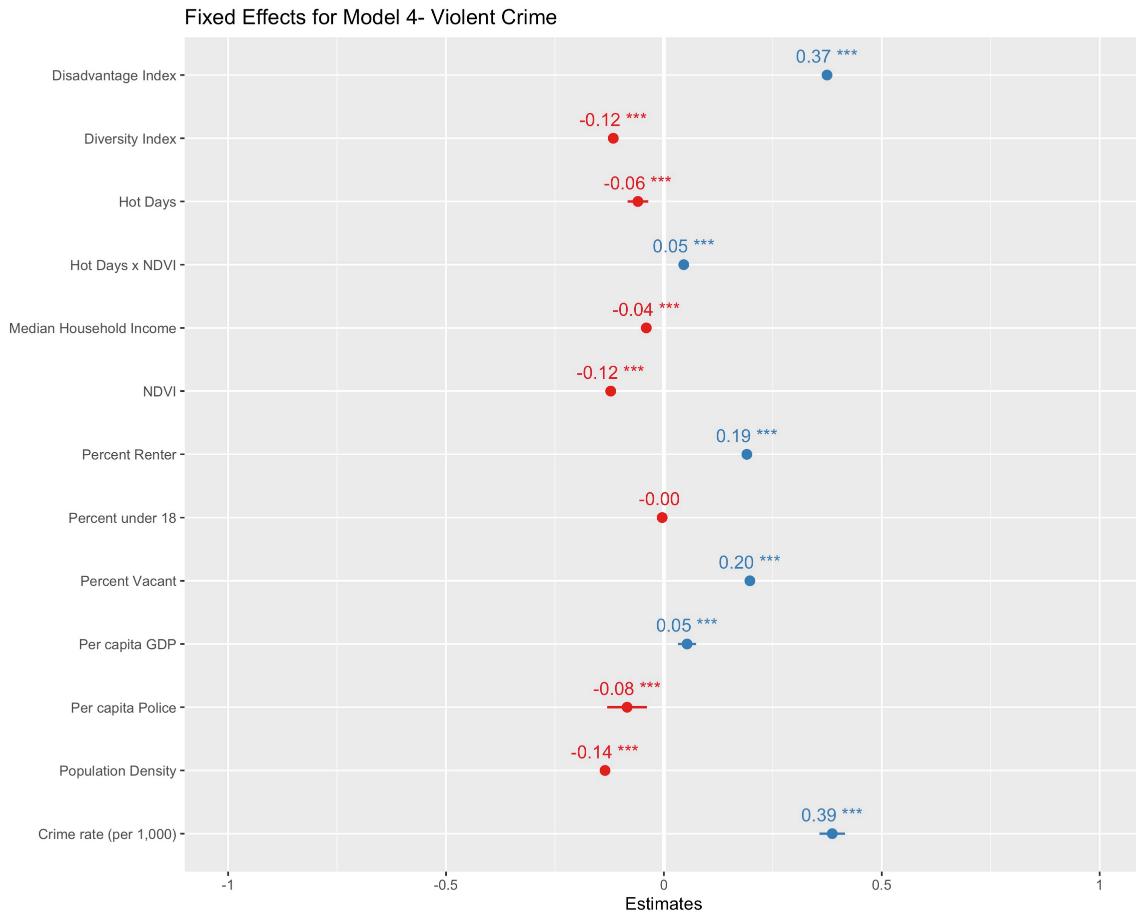

Figure 3.4b. Estimated fixed effects for violent crime risk, model 4 (standardized coefficients).

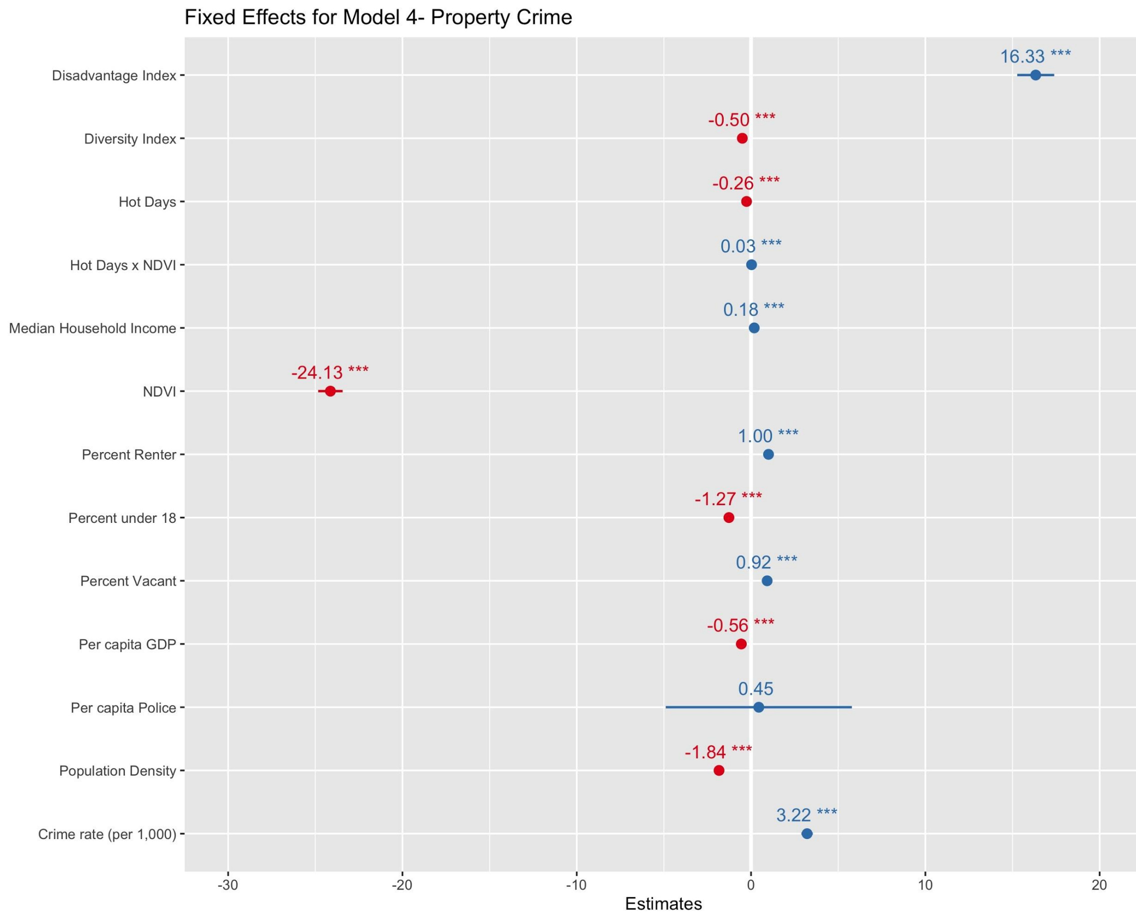

Figure 3.4c. Estimated fixed effects for property crime risk, model 4.

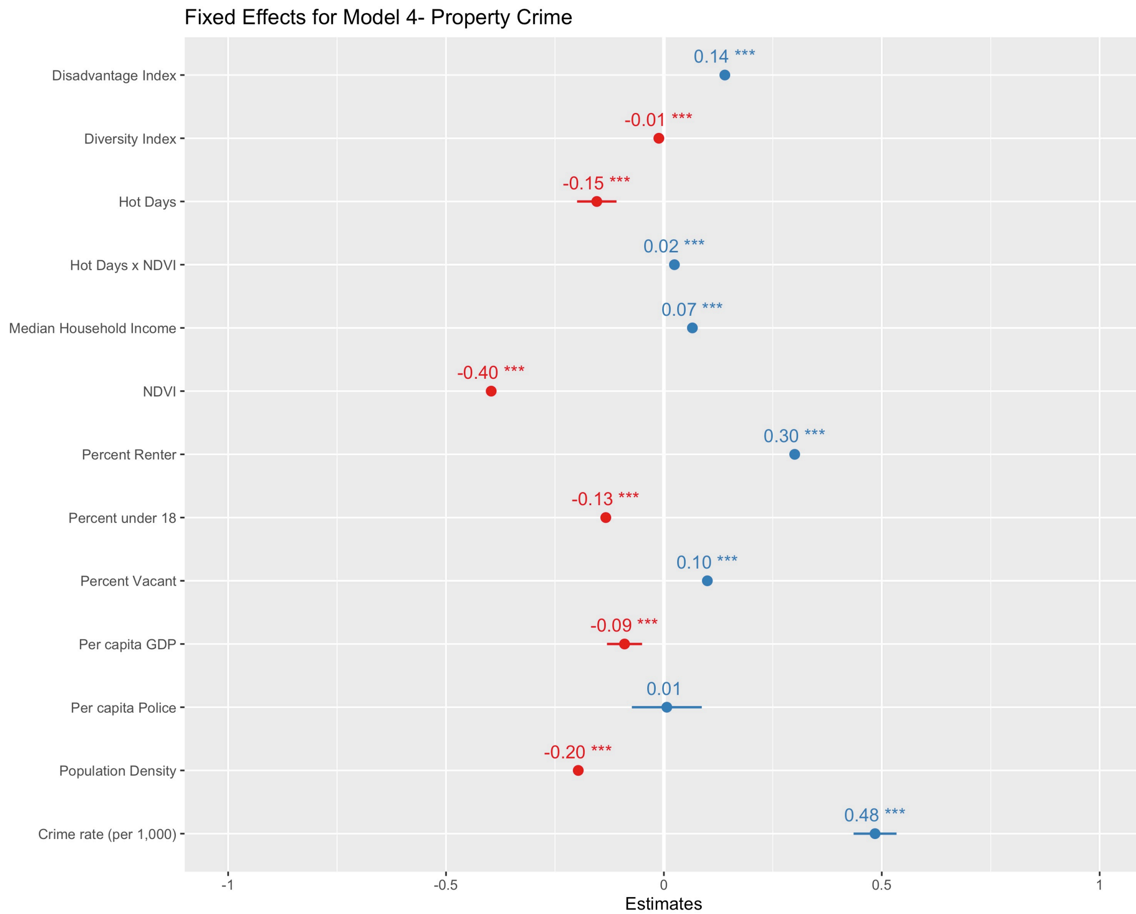

Figure 3.4d. Estimated fixed effects for property crime risk, model 4 (standardized coefficients).

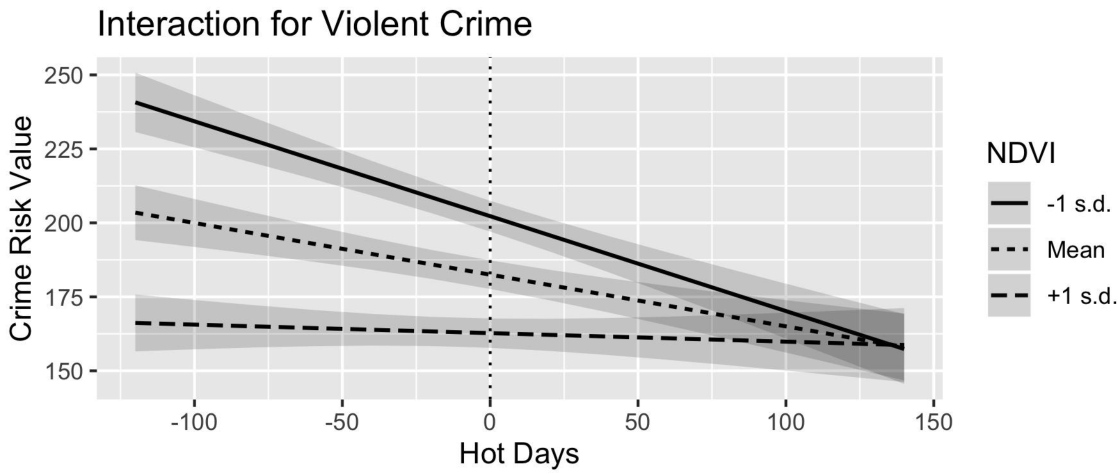

Figure 3.5a. Interaction plot of NDVI by Hot Days for violent crime

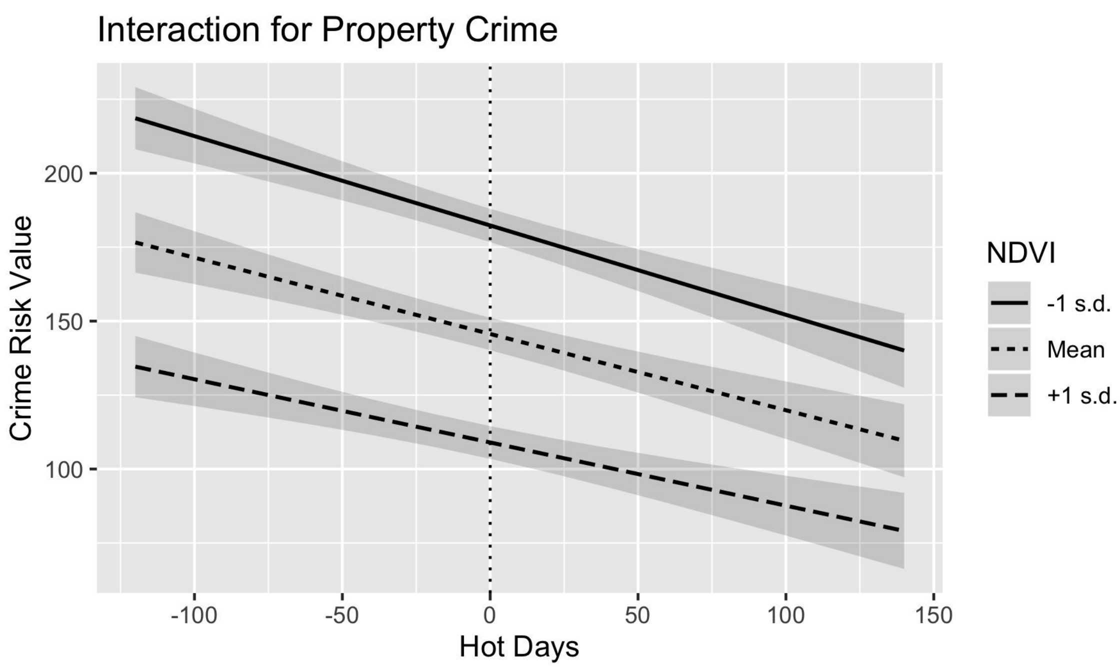

Figure 3.5b. Interaction plot of NDVI by Hot Days for property crime

Discussion

Our modeling results indicate that the association between hot days and crime depends on the level of greenspace in a block group. Areas that are greener have less crime on average and see little change in violent crime as hot days increase. For property crime, both green and not green areas see the same decreases in crime with more hot days.

The cross-level interaction of NDVI and hot days is significant and has a positive value, indicating that an increase in greenspace is associated with an increase in the slope between hot days and crime. As the relationship was already negative, this points to the correlation weakening as there is greater greenspace. The initial association between hot days and crime suggests that more days in high heat are correlated with decreases in crime risk. Adding NDVI to this relationship reduces the amount of change in crime as the number of hot days increases (see figure 3.3).

For violent crime this relationship points to different results for block groups with higher and lower greenspace. A greener area will have lower crime risk on average than a less green area. With covariates accounted for, the association between hot days and violent crime risk was -0.17 at the average level of NDVI. As more hot days are experienced, areas with above average greenspace would see no change in crime, while areas with below average greenspace would see a greater decrease in crime risk. This suggests that for violent crime, as block groups become greener, the effect of more hot days moves from a crime reduction towards no effect. This shift only varies by a small amount as the interaction coefficient is 0.10 (at one standard deviation increase in NDVI, one additional hot day would be associated with a 0.15 increase in the violent crime risk index, or 0.15 % change).

For property crime, the relationship between hot days and crime at average NDVI was significant, suggesting that average greenspace was associated with a decrease in crime risk with more hot days. The effect of changes in NDVI was smaller than for violent crime. At higher and lower than average NDVI values crime would maintain a similar relationship, with an increase in hot days correlated with a decrease in property crime risk (see figure 3.3). In this case, block groups had a small difference in the relationship regardless of the amount of greenspace.

These findings lend support to the perspective of Negative Affect Escape theory, where more uncomfortable conditions would discourage criminal activity (Anderson, 2001; Baron & Bell, 1975; Bell & Baron, 1977). In the case of violent crime, we see that block groups with less greenspace are associated with decreasing crime risk with more hot days. With less green vegetation, these areas would be expected to become much warmer and less comfortable than other areas containing tree canopy and green vegetation (Armson et al., 2012). Having less vegetation to cool local conditions through shade and evapotranspiration, the uncomfortable thermal conditions would reduce outdoor activity and lead to less interaction among people (Graff Zivin & Neidell, 2014; Huang, Lin, & Lien, 2015; Lin, 2009; Zacharias, Stathopoulos, & Wu, 2001). Areas with greater amounts of greenspace would have more comfortable thermal conditions, and therefore lead both to people leaving their homes and to social interactions that could increase the chance of becoming a target of criminal activity. As property crime showed the same relationship regardless of the amount of greenspace, uncomfortable hot weather would result in residents staying indoors at home, where most property crime occurs, and reducing the likelihood of property theft (The Bureau Of Justice Statistics, 2011).

It should be noted that there are realistic bounds to variables in the study that give some context to the amount of change that may be expected. The number of hot days are predicted to increase in the future, so a decrease is less likely (IPCC, 2014). This increase in the number of hot days would be expected to occur gradually over time so that changes year-to-year might be slight. NDVI is already bound at -1 to +1 with realistic values for vegetation existing between 0 and +1, so changes in greenspace are not likely beyond 3 to 4 units in the modeling (0.3 to 0.4 on the NDVI scale).

Limitations - There are some limitations with this research that hinge primarily on data availability for such studies. The crime data only provided a measure for the year, and lacked specific geographic or time details. A tradeoff was made to get a consistent measure applicable to a wide sample of cities, but this has the cost of not being able to capture temporal detail. The measure of greenspace also lacks temporal resolution as it captures the greenest period for the year. Using NDVI to assess greenspace has become common in multiple disciplines, but as a measure of just green vegetation it omits many nuances of accessibility and use (Dadvand et al., 2012; Fan, Das, & Chen, 2011). Lastly, weather data was used at the city level and does not capture microclimatic situations that would exist in neighborhoods due to urban structures like buildings.

Future research - Future research on this topic should look to incorporate a more detailed view of the processes related to urban greenspace. Using data with greater spatial and temporal resolution would allow for investigating seasonal and place specific attributes of the relationship. Greenspace could also be broken down into different types of data on land uses like parks were used. Both the formal and informal green areas of a city might play different roles in the relationship with crime.

Conclusion

Cities face an uncertain future in regards to extreme heat as climate changes. By reducing the urban heat island effect, greenspace can be one way to make neighborhoods more pleasant places to live under these future scenarios (Bowler et al., 2010; Brown et al., 2015; Harlan, Brazel, Prashad, Stefanov, & Larsen, 2006). In this study, however, we demonstrate how greenspace's capacity to improve thermal comfort can counteract the effect of unpleasantly hot thermal conditions to reduce crime. The results lend support to crime models that suggest decreases in crime at extreme temperatures, but they also show that improving local conditions through greenspace may have unintended (and perhaps unwanted) effects on crime.

Does this mean extreme heat should be a method of crime reduction? If the goal is to improve communities, then high heat is not the answer. Extreme heat events lead to more problems than solutions due to increased risks to residents' health (Harlan et al., 2007, 2006; Klinenberg, 1999). Our results show that greenspace makes communities more thermally pleasant, but also places that have less crime on average compared to areas with little greenspace. Adding and maintaining greenspace can reduce crime and improve many other aspects of life, making neighborhoods desirable places to live.

With interest in the effect of urban greenspace on public health and quality of life continuing to grow (Becker, Browning, Kuo, & Van Den Eeden, 2019; Engemann et al., 2019), it will be important to consider the complex interactions greenspace may have on other processes. These side effects and unintended outcomes, such as gentrification (Cole, Garcia Lamarca, Connolly, & Anguelovski, 2017), added costs for maintenance of greenspace (Pataki et al., 2011; Shackleton et al., 2016), or changes in crime, can impact city residents in ways that are difficult to predict. In efforts to improve cities and increase their resilience to anticipated climate changes, greenspace should be seen as one tool among a choice of interventions that can make the city a better place in the future.

References

Aguinis, H., Gottfredson, R. K., & Culpepper, S. A. (2013). Best-Practice Recommendations for Estimating Cross-Level Interaction Effects Using Multilevel Modeling. *Journal of Management*, *39*(6), 1490–1528.

Anderson, C. A. (1989). Temperature and aggression: ubiquitous effects of heat on occurrence of human violence. *Psychological Bulletin*, *106*(1), 74–96.

Anderson, C. A. (2001). Heat and violence. *Current Directions in Psychological Science, 10*(1), 33–38.

Anderson, C. A., & Anderson, D. C. (1984). Ambient temperature and violent crime: tests of the linear and curvilinear hypotheses. *Journal of Personality and Social Psychology, 46*(1), 91–97.

Anderson, C. A., Bushman, B. J., & Groom, R. W. (1997). Hot years and serious and deadly assault: empirical tests of the heat hypothesis. *Journal of Personality and Social Psychology, 73*(6), 1213–1223.

Andresen, M. A. (2015). Unemployment, GDP, and Crime: The Importance of Multiple Measurements of the Economy. *Canadian Journal of Criminology and Criminal Justice*, Vol. 57, pp. 35–58.

Armson, D., Stringer, P., & Ennos, A. R. (2012). The effect of tree shade and grass on surface and globe temperatures in an urban area. *Urban Forestry & Urban Greening, 11*(3), 245–255.

Baran, P. K., Tabrizian, P., Zhai, Y., Smith, J. W., & Floyd, M. F. (2018). An exploratory study of perceived safety in a neighborhood park using immersive virtual environments. *Urban Forestry & Urban Greening, 35*, 72–81.

Baron, R. A. (1972). Aggression as a function of ambient temperature and prior anger arousal. *Journal of Personality and Social Psychology, 21*(2), 183–189.

Baron, R. A., & Bell, P. A. (1975). Aggression and heat: mediating effects of prior provocation and exposure to an aggressive model. *Journal of Personality and Social Psychology, 31*(5), 825–832.

Baron, R. A., & Richardson, D. (1994). *Human Aggression, 2nd Edition*. New York, NY: Plenum Press.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software, 67*(1).

Becker, D. A., Browning, M. H. E. M., Kuo, M., & Van Den Eeden, S. K. (2019). Is green land cover associated with less health care spending? Promising findings from county-level Medicare spending in the continental United States. *Urban Forestry & Urban Greening*, *41, 39-47.*

Bell, P. A. (1992). In defense of the negative affect escape model of heat and aggression. *Psychological Bulletin, 111*(2), 342–346.

Bell, P. A. (2005). Reanalysis and perspective in the heat--aggression debate. *Journal of Personality and Social Psychology, 89*(1), 71–73.

Bell, P. A., & Baron, R. A. (1977). Aggression and ambient temperature: The facilitating and inhibiting effects of hot and cold environments. *Bulletin of the Psychonomic Society, 9*(6), 443–445.

Bell, P. A., & Fusco, M. E. (1986). Linear and curvilinear relationships between temperature, affect, and violence: Reply to Cotton. *Journal of Applied Social Psychology, 16*(9), 802–807.

Błażejczyk, K., Broede, P., Fiala, D., Havenith, G., Holmér, I., Jendritzky, G., … Kunert, A. (2010). Principles of the new Universal Thermal Climate Index (UTCI) and its application to bioclimatic research in European scale. *Miscellanea Geographica, 14*(2010), 91–102.

Błażejczyk, K., Jendritzky, G., Bröde, P., Fiala, D., Havenith, G., Epstein, Y., … Kampmann, B. (2013). An introduction to the Universal Thermal Climate Index (UTCI). *Geographia Polonica, 86*(1), 5–10.

Bowler, D. E., Buyung-Ali, L., Knight, T. M., & Pullin, A. S. (2010). Urban greening to cool towns and cities: A systematic review of the empirical evidence. *Landscape and Urban Planning, 97*(3), 147–155.

Branas, C. C., Cheney, R. A., MacDonald, J. M., Tam, V. W., Jackson, T. D., & Ten Have, T. R. (2011). A difference-in-differences analysis of health, safety, and greening vacant urban space. *American Journal of Epidemiology, 174*(11), 1296–1306.

Branas, C. C., South, E., Kondo, M. C., Hohl, B. C., Bourgois, P., Wiebe, D. J., & MacDonald, J. M. (2018). Citywide cluster randomized trial to restore blighted vacant land and its effects on violence, crime, and fear. *Proceedings of the National Academy of Sciences*, *115*(12), 2946-2951.

Bröde, P. (2009). *UTCI Universal Thermal Climate Index* (Version a 0.002). Retrieved from http://www.utci.org/

Bröde, P., Fiala, D., Błażejczyk, K., Holmér, I., Jendritzky, G., Kampmann, B., … Havenith, G. (2012). Deriving the operational procedure for the Universal Thermal Climate Index (UTCI). *International Journal of Biometeorology, 56*(3), 481–494.

Brown, R. D., Vanos, J., Kenny, N., & Lenzholzer, S. (2015). Designing urban parks that ameliorate the effects of climate change. *Landscape and Urban Planning, 138*(Supplement C), 118–131.

Brunsdon, C., Corcoran, J., Higgs, G., & Ware, A. (2009). The Influence of Weather on Local Geographical Patterns of Police Calls for Service. *Environment and Planning. B, Planning & Design, 36*(5), 906–926.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global Nonlinear Effect of Temperature on Economic Production. *Nature, 527*, 235.

Carlsmith, J. M., & Anderson, C. A. (1979). Ambient temperature and the occurrence of collective violence: a new analysis. *Journal of Personality and Social Psychology, 37*(3), 337–344.

Cassal, K. R. (2018). *2018 Esri Diversity Index*. Esri.

Chow, W. T. L., Pope, R. L., Martin, C. A., & Brazel, A. J. (2011). Observing and modeling the nocturnal park cool island of an arid city: horizontal and vertical impacts. *Theoretical and Applied Climatology, 103*(1-2), 197–211.

Cohn, E. G. (1990). Weather and Crime. *The British Journal of Criminology*, 30, 51–64.

Cole, H. V. S., Garcia Lamarca, M., Connolly, J. J. T., & Anguelovski, I. (2017). Are green cities healthy and equitable? Unpacking the relationship between health, green space and gentrification. *Journal of Epidemiology and Community Health, 71*(11), 1118–1121.

Cotton, J. L. (1986). Ambient temperature and violent crime. *Journal of Applied Social Psychology*, *16*(9), 786-801.

Dadvand, P., de Nazelle, A., Triguero-Mas, M., Schembari, A., Cirach, M., Amoly, E., … Nieuwenhuijsen, M. (2012). Surrounding greenness and exposure to air pollution during pregnancy: an analysis of personal monitoring data. *Environmental Health Perspectives, 120*(9), 1286–1290.

Declet-Barreto, J., Brazel, A. J., Martin, C. A., Chow, W. T. L., & Harlan, S. L. (2013). Creating the park cool island in an inner-city neighborhood: heat mitigation strategy for Phoenix, AZ. *Urban Ecosystems, 16*(3), 617–635.

de Freitas, C. R. (2003). Tourism climatology: evaluating environmental information for decision making and business planning in the recreation and tourism sector. *International Journal of Biometeorology, 48*(1), 45–54.

Di Napoli, C., Pappenberger, F., & Cloke, H. L. (2018). Assessing heat-related health risk in Europe via the Universal Thermal Climate Index (UTCI). *International Journal of Biometeorology, 62*(7), 1155–1165.

Donovan, G. H., & Prestemon, J. P. (2010). The Effect of Trees on Crime in Portland, Oregon. *Environment and Behavior, 44*(1), 3–30.

Engemann, K., Pedersen, C. B., Arge, L., Tsirogiannis, C., Mortensen, P. B., & Svenning, J.-C. (2019). Residential green space in childhood is associated with lower risk of psychiatric disorders from adolescence into adulthood. *Proceedings of the National Academy of Sciences*, *116*(11), 5188-5193.

Epstein, Y., & Moran, D. S. (2006). Thermal comfort and the heat stress indices. *Industrial Health, 44*(3), 388–398.

Esri. (2015, April 29). *2017 USA Crime Index*. Retrieved from https://www.arcgis.com/home/item.html?id=b3802d8a309544b791c2304fece864dc

Fan, Y., Das, K. V., & Chen, Q. (2011). Neighborhood green, social support, physical activity, and stress: assessing the cumulative impact. *Health & Place, 17*(6), 1202–1211.

Federal Bureau of Investigation. (2004). *Uniform Crime Reporting Handbook*. Retrieved from https://www2.fbi.gov/ucr/handbook/ucrhandbook04.pdf

Federal Bureau of Investigation. (2016). *Crime in the United States, 2015* [Data set]. Crime in the United States, 2015. Retrieved from https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015

Felson, M., & Boba, R. L. (2010). *Crime and everyday life*. Sage.

Fisichelli, N. A., Schuurman, G. W., Monahan, W. B., & Ziesler, P. S. (2015). Protected Area Tourism in a Changing Climate: Will Visitation at US National Parks Warm Up or Overheat? *PloS One, 10*(6), e0128226.

Gamble, J. L., & Hess, J. J. (2012). Temperature and violent crime in Dallas, Texas: relationships and implications of climate change. *The Western Journal of Emergency Medicine, 13*(3), 239–246.

Gilstad-Hayden, K., Wallace, L. R., Carroll-Scott, A., Meyer, S. R., Barbo, S., Murphy-Dunning, C., & Ickovics, J. R. (2015). Research note: Greater tree canopy cover is associated with lower rates of both violent and property crime in New Haven, CT. *Landscape and Urban Planning, 143*, 248–253.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18-27.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics, 32*(1), 1–26.

Hajat, S., O'Connor, M., & Kosatsky, T. (2010). Health effects of hot weather: from awareness of risk factors to effective health protection. *The Lancet, 375*(9717), 856–863.

Harlan, S. L., Brazel, A. J., Jenerette, D. G., Jones, N. S., Larsen, L., Prashad, L., & Stefanov, W. L. (2007). *In the shade of affluence: the inequitable distribution of the urban heat island*. In R. Wilkinson & W. Freudenburg (Eds.), Equity and the Environment (pp. 173–202). Emerald Group Publishing Limited.

Harlan, S. L., Brazel, A. J., Prashad, L., Stefanov, W. L., & Larsen, L. (2006). Neighborhood microclimates and vulnerability to heat stress. *Social Science & Medicine, 63*(11), 2847–2863.

Harries, K. D., Stadler, S. J., & Zdorkowski, R. T. (1984). Seasonality and Assault: Explorations in Inter-Neighborhood Variation, Dallas 1980. *Annals of the Association of American Geographers, 74*(4), 590–604.

Holtan, M. T., Dieterlen, S. L., & Sullivan, W. C. (2014). Social Life Under Cover: Tree Canopy and Social Capital in Baltimore, Maryland. *Environment and Behavior, 47*(5), 502–525.

Horrocks, J., & Menclova, A. K. (2011). The effects of weather on crime. *New Zealand Economic Papers, 45*(3), 231–254.

Hox, J. J., Moerbeek, M., & van de Schoot, R. (2010). *Multilevel Analysis: Techniques and Applications, Second Edition*. Routledge.

Hsiang, S. M., Burke, M., & Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science, 341*(6151), 1235367.

Huang, K.-T., Lin, T.-P., & Lien, H.-C. (2015). Investigating Thermal Comfort and User Behaviors in Outdoor Spaces: A Seasonal and Spatial Perspective. *Advances in Meteorology*, 2015.

IPCC. (2014). *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. Retrieved from http://www.ipcc.ch/pdf/assessment-report/ar5/syr/SYR_AR5_FINAL_full_wcover.pdf

Jendritzky, G., Maarouf, A., & Staiger, H. (2001). *Looking for a Universal Thermal Climate Index UTCI for Outdoor Applications*. Presented at the Windsor-Conference on Thermal Standards, Windsor, UK.

Jenerette, G. D., Harlan, S. L., Brazel, A., Jones, N., Larsen, L., & Stefanov, W. L. (2007). Regional relationships between surface temperature, vegetation, and human settlement in a rapidly urbanizing ecosystem. *Landscape Ecology, 22*(3), 353–365.

Kaplan, S. (1995). The restorative benefits of nature: Toward an integrative framework. *Journal of Environmental Psychology, 15*(3), 169–182.

Klinenberg, E. (1999). Denaturalizing disaster: A social autopsy of the 1995 Chicago heat wave. *Theory and Society, 28*(2), 239–295.

Kondo, M. C., Han, S., Donovan, G. H., & MacDonald, J. M. (2017). The association between urban trees and crime: Evidence from the spread of the emerald ash borer in Cincinnati. *Landscape and Urban Planning, 157*, 193–199.

Kovats, R. S., & Hajat, S. (2008). Heat stress and public health: a critical review. *Annual Review of Public Health, 29*, 41–55.

Krivo, L. J., Peterson, R. D., & Kuhl, D. C. (2009). Segregation, racial structure, and neighborhood violent crime. *American Journal of Sociology, 114*(6), 1765–1802.

Kuo, F. E., & Sullivan, W. C. (2001a). Aggression and violence in the inner city: Effects of environment via mental fatigue. *Environment and Behavior, 33*(4), 543–571.

Kuo, F. E., & Sullivan, W. C. (2001b). Environment and Crime in the Inner City. *Environment and Behavior, 33*(3), 343–367.

Levitt, S. D. (1997). Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime. *The American Economic Review, 87*(3), 270–290.

Lin, T.-P. (2009). Thermal perception, adaptation and attendance in a public square in hot and humid regions. *Building and Environment, 44*(10), 2017–2026.

Locke, D. H., Han, S., Kondo, M. C., Murphy-Dunning, C., & Cox, M. (2017). Did community greening reduce crime? Evidence from New Haven, CT, 1996–2007. *Landscape and Urban Planning, 161*, 72–79.

Maas, J., Spreeuwenberg, P., van Winsum-Westra, M., Verheij, R. A., Vries, S., & Groenewegen, P. P. (2009). Is Green Space in the Living Environment Associated with People's Feelings of Social Safety? *Environment & Planning A, 41*(7), 1763–1777.

Mak, B., & Jim, C. Y. (2018). Examining fear-evoking factors in urban parks in Hong Kong. *Landscape and Urban Planning, 171*, 42–56.

Mares, D. (2013). Climate change and levels of violence in socially disadvantaged neighborhood groups. *Journal of Urban Health: Bulletin of the New York Academy of Medicine, 90*(4), 768–783.

Mares, D. M., & Moffett, K. W. (2019). Climate Change and Crime Revisited: An Exploration of Monthly Temperature Anomalies and UCR Crime Data. *Environment and Behavior, 51*(5), 502–529.

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., … Fuertes, E. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research, 158*, 301–317.

Mavroudeas, S., Papastamatelou, J., Unger, A., Tsouvelas, G., Konstantakopoulos, G., & Giotakos, O. (2018). (Summer) Time for murder: Is there a link between increased temperature and homicides? *Dialogues in Clinical Neuroscience & Mental Health, 1*(4), 128–137.

McDowall, D., & Loftin, C. (2009). Do US City Crime Rates Follow a National Trend? The Influence of Nationwide Conditions on Local Crime Patterns. *Journal of Quantitative Criminology, 25*(3), 307–324.

McGregor, G. R., Bessemoulin, P., Ebi, K., & Menne, B. (Eds.). (2015). *Heatwaves and Health: Guidance on Warning-System Development*. Retrieved from https://www.who.int/globalchange/publications/WMO_WHO_Heat_Health_Guidance_2015.pdf

McGregor, G. R., & Vanos, J. K. (2018). Heat: a primer for public health researchers. *Public Health, 161*, 138–146.

Meehl, G. A., & Tebaldi, C. (2004). More intense, more frequent, and longer lasting heat waves in the 21st century. *Science, 305*(5686), 994–997.

Michael, S. E., Hull, R. B., & Zahm, D. L. (2001). Environmental factors influencing auto burglary A case study. *Environment and Behavior, 33*(3), 368–388.

NASA/GSFC. (2013). NLDAS-2: *North American Land Data Assimilation System Forcing Fields* [Data set]. https://doi.org/10.1029/2010EO340001

Nasar, J. L., Fisher, B., & Grannis, M. (1993). Proximate physical cues to fear of crime. *Landscape and Urban Planning, 26*(1), 161–178.

Nassauer, J. I. (1995). Messy Ecosystems, Orderly Frames. *Landscape Journal, 14*(2), 161–170.

Parsons, K. (2014). *Human Thermal Environments: The Effects of Hot, Moderate, and Cold Environments on Human Health, Comfort, and Performance, Third Edition*. CRC Press.

Pataki, D. E., Boone, C. G., Hogue, T. S., Jenerette, G. D., McFadden, J. P., & Pincetl, S. (2011). Socio-ecohydrology and the urban water challenge. *Ecohydrology, 4*(2), 341–347.

Pearsall, H., & Christman, Z. (2012). Tree-lined lanes or vacant lots? Evaluating non-stationarity between urban greenness and socio-economic conditions in Philadelphia, Pennsylvania, USA at multiple scales. *Applied Geography, 35*(1), 257–264.

Quetelet, L. A. J. (1842). *A treatise on man and the development of his faculties*. William and Robert Chambers.

Ranson, M. (2014). Crime, weather, and climate change. *Journal of Environmental Economics and Management, 67*(3), 274–302.

R Core Team. (2017). *R: A language and environment for statistical computing* (Version 3.4). Retrieved from https://www.R-project.org/

Reinhart, C. F., Dhariwal, J., & Gero, K. (2017). Biometeorological indices explain outside dwelling patterns based on Wi-Fi data in support of sustainable urban planning. *Building and Environment, 126*(Supplement C), 422–430.

Rosselló-Nadal, J. (2014). How to evaluate the effects of climate change on tourism. *Tourism Management, 42*, 334–340.

Rotton, J., & Cohn, E. (2000a). Violence is a curvilinear function of temperature in Dallas: a replication. *Journal of Personality and Social Psychology, 78*(6), 1074–1081.

Rotton, J., & Cohn, E. G. (2000b). Weather, Disorderly Conduct, and Assaults: From Social Contact to Social Avoidance. *Environment and Behavior, 32*(5), 651–673.

Rutty, M., & Scott, D. (2015). Bioclimatic comfort and the thermal perceptions and preferences of beach tourists. *International Journal of Biometeorology, 59*(1), 37–45.

Sampson, N., Nassauer, J., Schulz, A., Hurd, K., Dorman, C., & Ligon, K. (2017). Landscape care of urban vacant properties and implications for health and safety: Lessons from photovoice. *Health & Place, 46*, 219–228.

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: a multilevel study of collective efficacy. *Science, 277*(5328), 918–924.

Schusler, T., Weiss, L., Treering, D., & Balderama, E. (2017). Research note: Examining the association between tree canopy, parks and crime in Chicago. *Landscape and Urban Planning, 170*, 309-313.

Shackleton, C. M., Ruwanza, S., Sinasson Sanni, G. K., Bennett, S., De Lacy, P., Modipa, R., … Thondhlana, G. (2016). Unpacking Pandora's Box: Understanding and Categorising Ecosystem Disservices for Environmental Management and Human Wellbeing. *Ecosystems, 19*(4), 587–600.

Simpson, E. H. (1949). Measurement of diversity. *Nature*. *163*(4148), 688.

Singer, J. D., & Willett, J. B. (2003). *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. Oxford University Press.

Snijders, T., & Bosker, R. (2012). *Multilevel analysis: an introduction to basic and advanced multilevel modelling*. Sage.

Taylor, L., & Hochuli, D. F. (2017). Defining greenspace: Multiple uses across multiple disciplines. *Landscape and Urban Planning, 158*, 25–38.

The Bureau Of Justice Statistics. (2011). *Bureau of Justice Statistics (BJS) - Location*. Retrieved from https://www.bjs.gov/index.cfm?ty=tp&tid=44

Troy, A., Grove, J. M., & O'Neil-Dunne, J. (2012). The relationship between tree canopy and crime rates across an urban–rural gradient in the greater Baltimore region. *Landscape and Urban Planning, 106*(3), 262–270.

Tsai, W.-L., McHale, M. R., Jennings, V., Marquet, O., Hipp, J. A., Leung, Y.-F., & Floyd, M. F. (2018). Relationships between Characteristics of Urban Green Land Cover and Mental Health in U.S. Metropolitan Areas. *International Journal of Environmental Research and Public Health, 15*(2). 340.

U S Department of Commerce. (2015). *Measuring the Economy: A Primer on GDP and the National Income and Product Accounts*. Retrieved from https://www.bea.gov/national/pdf/nipa_primer.pdf

U S Kerner Commission. (1968). *Report of the national advisory commission on civil disorders*. Retrieved from http://www.eisenhowerfoundation.org/docs/kerner.pdf

Verbos, R. I., Altschuler, B., & Brownlee, M. T. J. (2017). Weather Studies in Outdoor Recreation and Nature-Based Tourism: A Research Synthesis and Gap Analysis. *Leisure Sciences*, *40*(6), 533-556.

Weier, J., & Herring, D. (2000, August 30). *Measuring vegetation (NDVI & EVI)*. Retrieved https://earthobservatory.nasa.gov/Features/MeasuringVegetation/

Wolfe, M. K., & Mennis, J. (2012). Does vegetation encourage or suppress urban crime? Evidence from Philadelphia, PA. *Landscape and Urban Planning, 108*(2–4), 112–122.

Wong, E., Akbari, H., Bell, R., & Cole, D. (2011). *Reducing Urban Heat Islands: Compendium of Strategies*. Retrieved from https://www.epa.gov/sites/production/files/2014-06/documents/basicscompendium.pdf

Younan, D., Tuvblad, C., Li, L., Wu, J., Lurmann, F., Franklin, M., … Chen, J.-C. (2016). Environmental Determinants of Aggression in Adolescents: Role of Urban Neighborhood Greenspace. *Journal of the American Academy of Child and Adolescent Psychiatry, 55*(7), 591–601.

Zacharias, J., Stathopoulos, T., & Wu, H. (2001). Microclimate and Downtown Open Space Activity. *Environment and Behavior, 33*(2), 296–315.

CHAPTER FOUR

PARKS AS SAFE HAVENS OR CRIME MAGNETS: PROXIMITY TO PARKS AND CRIME IN FOUR CITIES

Abstract

Urban parks, as a type of greenspace, provide benefits to residents, but can also be attractors for undesirable activities and crime. We examined the relationship between crime and proximity to parks within four cities during 2016 to investigate how parks and crime are related. Results point to higher amounts of violent and property crime closer to parks, considering covariates of crime such as income, population density, and social disadvantage. The research highlights how amenities such as parks can also have drawbacks that should be considered when seeking to improve the quality of life for urban residents. Future research could explore specific local effects of parks and combine such research with qualitative studies on park quality and the perception of crime.

Introduction

Crime is a threat to well-being and quality of life (Jackson & Stafford, 2009), and with expected growth in urban areas, ensuring safe and high-quality communities will be important for current and future residents (United Nations, 2015). Researchers and city leaders suggest that greenspace is one way to improve local neighborhoods, providing space for physical activity and improved health (City Parks Alliance, 2019; Kaczynski, Potwarka, & Saelens, 2008; Sugiyama, Carver, Koohsari, & Veitch, 2018). While greenspace can include many types of urban land uses, such as private yards, gardens, or vacant lots, parks are an often-cited example in the literature, representing a type of greenspace managed for public use (Taylor & Hochuli, 2017).

Research on the interaction of urban parks and crime points to parks being associated with both increases and decreases in crime (Bogar & Beyer, 2016; Han, Cohen, Derose, Li, & Williamson, 2018). Prior studies have focused on isolated cities and used a variety of research methods, making comparison of findings difficult and not considering contextual factors that may vary across cities. To address this gap, we examined four cities using detailed spatial data on land use and crime incidents to address the question of how proximity to urban parks and crime are related.

Background

Greenspace and *parks* are ambiguous terms in the literature, often being used interchangeably (Taylor & Hochuli, 2017). Greenspace connotes areas in vegetation which can include public and private lands. Parks may or may not contain vegetation and are primarily public lands with space for activity or relaxation (Forsyth, Musacchio, & Fitzgerald, 2005; Konijnendijk, Annerstedt, Nielsen, & Maruthaveeran, 2013).

Urban parks are a subset of land use within the concept of open space and are frequently provided as an example of greenspace (Taylor & Hochuli, 2017). Traditionally, urban parks contain some measure of 'greenness' or vegetation that can be seen as representing a natural condition, though parks are often highly designed landscapes (Forsyth et al., 2005). This is reflected in common definitions of *park* such as, "a large public green area..." and “an area maintained in its natural state as a public property” (Jewell & Abate, 2001; Merriam-Webster Dictionary, n.d). Parks are historically portrayed as a necessary part of cities to combat the ills of urban life (K. Jones & Wills, 2005). Today urban parks continue to be viewed as remedies to the stress of living in dense areas, providing places for activity, socializing, and relaxation (Boulton, Dedekorkut-Howes, & Byrne, 2018; Harnik, 2012; Keith, Larson, Shafer, Hallo, & Fernandez, 2018).

Urban parks are typically accessible to the public and managed by a municipal agency (Forsyth et al., 2005). Further definition is offered by those involved in the promotion and study of urban parks to include aspects such as:

> "...land owned by regional, state, and federal agencies ...including school grounds formally open to the public and greenways that function as parks." (The Trust for Public Land, 2017)

> "... delineated open space areas, mostly dominated by vegetation and water, and generally reserved for public use. Urban parks are mostly larger, but can also have the shape of smaller 'pocket parks'. Urban parks are usually locally defined (by authorities) as 'parks'." (Konijnendijk et al., 2013)

While parks are used as an example of greenspace, it is clear that they can be separate types of land use within a city. A conceptual view of urban open space, greenspace, and parks is represented in figure 4.1. As illustrated, greenspace and parks are forms of urban open space. Parks themselves can be greenspaces, but are not always vegetated places.

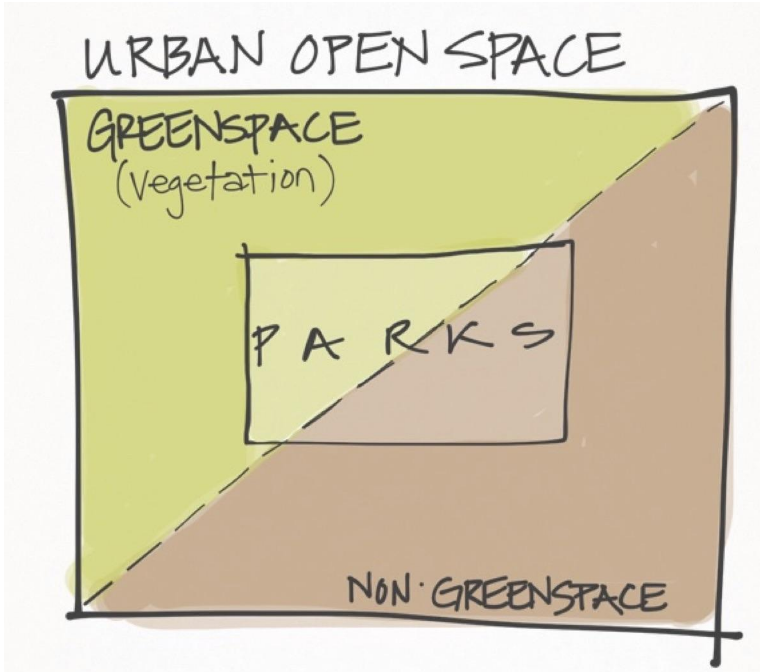

Figure 4.1 - Conceptual figure of open space, greenspace, and parks (source: author)

Urban parks and crime

As a type of greenspace, urban parks provide many benefits to the community, but are also perceived as the setting for undesirable behaviors and activities such as attracting the homeless, drug markets, prostitution, and idle youth (Harnik, 2012; Stodolska, Acevedo, & Shinew, 2009). The reputation of urban parks as crime magnets has also been sensationalized by news media, placing an over emphasis on crime in parks despite equal or greater amounts of crime outside of them (K. Jones & Wills, 2005). Crime, both real and perceived, can be a barrier to community members visiting and benefiting from urban parks (Han et al., 2018; Ou et al., 2016).

An alternative viewpoint to parks as crime magnets frames parks as deterrents of crime. Criminological theory provides some perspective on how parks can deter crime through the Routine Activity Theory. This theory proposes that crime is the result of three elements: “likely offenders, suitable targets and the absence of capable guardians against crime” (Cohen & Felson, 1979, p. 588). Parks can be seen through the lens of Routine Activity as attracting people through events and activities, increasing the number of guardians keeping watch and therefore discouraging crime. This is captured by the term “eyes on the street” where more people can increase surveillance of public spaces (Jacobs, 1961). In contrast, park activities could also increase the number of targets for criminals.

Social disorganization theory provides another view of how parks can reduce crime, suggesting that crime results from low socio-economic conditions and breakdowns in social control (Shaw & McKay, 1972). Parks are thought to help build and support social connections in a neighborhood thereby increasing informal control that deters crime (Cohen, Inagami, & Finch, 2008). Alternatively, parks could be victims of their surroundings, with disadvantaged neighborhoods attracting crime to common spaces like parks (Boessen & Hipp, 2018)

Crime prevention through environmental design (CPTED) is another perspective that can help explain the relationship between parks and crime through residents’ ability to maintain control over public areas (Newman, 1972). The design and programming of parks can lead to natural surveillance that can help deter crime and provide guardianship over space (Casteel & Peek-Asa, 2000). If parks limit visibility or provide many routes of movement they could conversely become spaces that encourage crime (Mair & Mair, 2003).

Parks and recreational areas are one urban land use that can influence that amount of crime in a community or city (Blair, Wilcox, & Eck, 2017; Brantingham & Brantingham, 1995). Prior research finds the relationship between crime and parks to be uncertain, with parks leading to increases or decreases in crime.

Neighborhood parks in Philadelphia were found to be places that generated crime, having higher concentrations of crime in the park vicinity versus other parts of the city (Groff & McCord, 2012). This same conclusion was made in a similar study comparing parks in Louisville, KY and Philadelphia (McCord & Houser, 2015). Parks can lead to increases in perceived (Baran, Tabrizian, Zhai, Smith, & Floyd, 2018) and real crime (Ceccato, 2014) when vegetation contributes to reduced visibility by park users.

Alternatively, an earlier study in Boston found no increase in crime for residents living near a popular greenway compared to neighboring streets (Crewe, 2001). An analysis of land uses and crime concluded that green areas and parks served more as deterrents of crime when compared to other land uses (Sypion-Dutkowska & Leitner, 2017). Other research finds that the relationship depends on the context of the surrounding neighborhood. In areas of higher deprivation and visible physical disorder, parks may not provide the same level of crime deterring benefits, becoming sources of criminal activity or displacing crime (Demotto & Davies, 2006; Harris, Larson, & Ogletree, 2017; Tower & Groff, 2014). The relationship with crime can also vary by type of criminal activity, with parks in Chicago found to have an association with property crimes but not other crime types such as assault or robbery (Harris et al., 2017; Schusler, Weiss, Treering, & Balderama, 2017). These many different conclusions point to the complex association that parks have with crime in the city (Kimpton, Corcoran, & Wickes, 2016).

To investigate how crime and parks are related within urban areas, we examined the relationship between proximity to parks and crime in four cities. As parks are viewed as a type of greenspace, we included measures of greenness at both the park and census block group level.

Methods

To examine how crime and urban parks are related, data were collected in four cities in the contiguous U.S. that represent different regions of the country. Census block groups that are greater than 50% within the city boundaries were used as the unit of analysis, totaling 3,373 block groups across the four cities. Missingness in some variable occurred due to block groups having 0 population or censored income values, resulting in 3,199 block groups used in the analysis. Data collected included crime incidents, sociodemographic variables, park spatial features, and greenspace measures.

*Case Citie*s - Cities were chosen that capture different contexts that parks may exist in. The cities chosen were Austin, TX, Philadelphia, PA, Phoenix, AZ, and San Francisco, CA. Requirements included that the cities be based in one of the four climate regions, have similar total population, and have adequate crime data available (see table 4.1 and figure 4.1). To capture different conditions of greenness that parks may exist under, the four cities fall into one of four climate regions defined by clustering mean temperature, mean precipitation, and the number of days with maximum temperatures over 90ºF. These weather variable averages are derived over the years 1981 - 2010, effectively representing the climate of a city (PRISM climate group, n.d.). K-means clustering was applied with the *kmeans* function in R statistical software version 3.5.0 (R Core Team, 2017) to determine four categories of climatic conditions based on precipitation (wet-dry), temperature (warm-cool), and number of days over 90ºF (high-low).

Table 4.1. City descriptive statistics

City	Austin, Texas	Philadelphia, Pennsylvania	Phoenix, Arizona	San Francisco, California
Population	947,897	1,567,872	1,615,041	870,887
Population Density per sq. mi.	3,182	11,692	3,126	18,573
Climate region	warm-wet-high	cool-wet-low	warm-dry-high	cool-dry-low
Census block groups	480	1221	944	554
Parks	393	558	217	476
Area (sq. mi.)	297.9	134.1	516.7	46.89
Mean Temperature (ºF)	68.3	56.0	72.3	57.0
Mean Precipitation (in)	33.5	46.7	9.2	24.6
Mean number of days over 90ºF	109	23	147	1
Mean city NDVI	0.533	0.412	0.212	0.243
Total number of crimes (FBI Part 1)	36,325	85,003	58,520	69,932

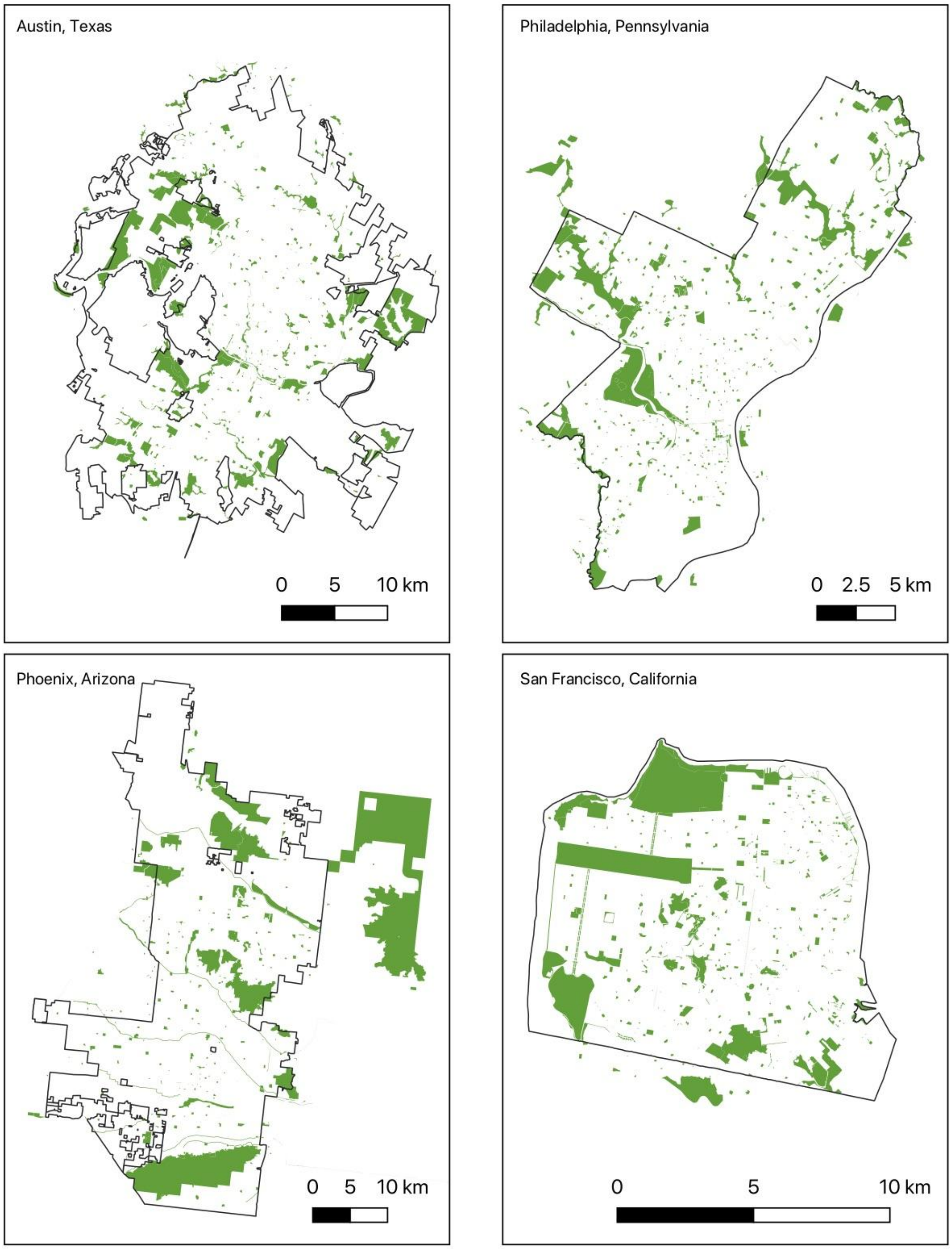

Figure 4.2. Map of cities and their parks

Data

Crime data - Crime incident data was obtained from each city, for the year 2016. This data contained date and location information, providing temporal and spatial attributes that allow analysis across the city landscape. Many cities have begun to provide data through open data platforms that include information on crimes. This approach to providing crime data is more prevalent in larger municipalities (Goldstein, Dyson, & Nemani, 2013). Despite the availability, the crime data required substantial cleaning to get all four cities into a common format. This included processing to common variables across cities, geocoding incidents missing latitude and longitude data, and removing crimes not included in the analysis (using only FBI Part 1 crimes (Federal Bureau of Investigation, 2004)). In the case of Phoenix crime data did not contain coordinate information and required the geocoding of address location in ArcGIS software (Hipp et al., 2016).

Crime points were aggregated to census block groups to produce crime counts for total, violent, and property crimes. The crime types are based on the classification used in the Uniform Crime Reporting systems with violent crimes composed of murder, aggravated assault, and robbery, and property crimes composed of larceny, burglary, auto theft, and arson (Federal Bureau of Investigation, 2004). Crimes relating to rape and sexual assault were omitted as they lack location information due to censoring by law enforcement agencies.

Park data - Data on parks was obtained from the Trust for Public Land (TPL) ParkServe database, which includes spatial data on parks for over 13,000 municipalities in the US (The Trust for Public Land, 2019) . Proximity to parks was calculated for block groups as the Euclidean distance to the nearest park using the *sf* package (version 0.6.4) in R (Pebesma, 2018). Once the nearest park was identified, the attributes of that park's size and NDVI value were added to the block group.

Greenness - Including a measure of greenness through a vegetation index allowed for the greenspace component of parks to be included in the analysis. The normalized difference vegetation index (NDVI) was used as the measure of greenness to assess both block groups and parks. NDVI is calculated from remote sensing imagery that captures the red and near infrared wavelengths of light. Green vegetation reflects these light bands in a unique combination that can be used as a measure of greenspace (Weier & Herring, 2000). The resulting values range from -1 to 1, with corresponding values: less than 0.0 water or impervious surface, 0.0 - 0.2 dry soil, 0.2-0.4 shrub and grasslands, 0.4-0.8 dense vegetation, 0.8+ forests (H. Jones & Vaughan, 2010; Weier & Herring, 2000). NDVI is regularly used within the social sciences and public health fields for assessing greenspace in urban areas (Beyer et al., 2014; Gascon et al., 2016; Taylor & Hochuli, 2017; Wolfe & Mennis, 2012; Younan et al., 2016).

Data for NDVI was sourced from Sentinel-2 imagery for 2016, which has a 10-meter spatial resolution (Copernicus, 2016). The imagery was processed within the Google Earth Engine platform (Gorelick et al., 2017) to obtain the greenest pixel for the entire year. NDVI was averaged within block groups and within park features, then multiplied by 10 to aid in interpretability.

Sociodemographic - Social variables were sourced from the 2012-2016 American Community Survey (ACS) at the census block group level. These included 1) median household income, 2) population density, 3) percent under 18, 4) percent of housing vacant, 5) percent renter occupied housing, 6) a racial/ethnic diversity index, and 7) a disadvantage index. The diversity index was composed of 14 group categories as measured by the ACS and represents the probability of 2 selected individuals belonging to different groups (Cassal, 2018). The disadvantage index was constructed from 1) percent unemployed, 2) percent with less than a high school diploma, 3) percent female headed households, and 4) percent of families below the poverty line, being the mean of the standardized value of each variable (Krivo, Peterson, & Kuhl, 2009; Sampson, Raudenbush, & Earls, 1997).

The independent variables used in the analysis were: median household income, percent under 18, percent of housing vacant, percent renter occupied housing, diversity index, disadvantage index, population density per square kilometer, block group NDVI, size of nearest park in acres, nearest park NDVI, and distance to the nearest park. The dependent variables were the count of violent crime and property crime in block groups. Missing values occur due to censoring of median household income or block groups with zero population, resulting in a total number of block groups used in the analysis being 3,199 across the four cities.

Analysis Strategy

Due to the dependent variable of crime being the count of incidents, a generalized linear model was used with a poisson distribution. Overdispersion was observed in the poisson model, indicating that a negative binomial model may better fit the data. Models were fit with the *glm.nb* function from the MASS package in R statistical software (R Core Team, 2017; Vernables & Ripley, 2002). The model estimates if a block group has more or less violent or property crime. Exponentiating the coefficients from the negative binomial regression provides a rate of change in the dependent for one unit change in a predictor, when all other variables are held constant in the model.

To account for differences in crime counts due to different sizes of block groups, block group area was used as an offset within the models. This results in the model predicting crime densities, being crimes per square kilometer, as incident rate ratios (IRR) for the rate of change in crime for a one unit change in the predictor variable. Models were fit to each city for violent and property crime.

Independent variables were mean centered within each city. This results in the model intercept being the predicted count of crimes per square kilometer for block groups that are average on all variables.

Results

Descriptive statistics of data

Descriptive statistics for the cities are presented in table 4.2. The city with the highest green vegetation measure was Austin, with a mean NDVI value across the block groups of the city of 0.533. The city with the lowest green vegetation measure was Phoenix at 0.212. The number of parks ranged from 217 in Phoenix to 558 in Philadelphia. Austin and Phoenix had similar densities of total crime across the city, approximately 93 per square kilometer, while San Francisco had the highest at 889 crimes per square kilometer.

Table 4.2. Descriptive statistics for case cities

Variable		Austin, TX	Philadelphia, PA	Phoenix, AZ	San Francisco, CA
Block Group Area (sq. km.)	Mean	1.57	0.26	1.41	0.21
	SD	2.81	0.71	4.23	0.42
	Min	0.09	0.02	0.09	0.02
	Max	25.34	17.33	65.53	6.11
Distance to Park (km.)	Mean	0.56	0.28	0.70	0.23
	SD	0.64	0.21	0.56	0.17
	Min	0.00	0.00	0.00	0.00
	Max	4.96	1.80	6.76	0.98
Disadvantage Index	Mean	0.02	0.06	0.04	-0.01
	SD	0.72	0.78	0.79	0.73
	Min	-0.99	-1.26	-1.15	-1.00
	Max	3.23	2.91	3.35	4.52
Diversity Index	Mean	0.52	0.39	0.52	0.57
	SD	0.17	0.24	0.19	0.13
	Min	0.05	0.00	0.00	0.08
	Max	0.80	0.83	0.83	0.81
Mean NDVI (block group)	Mean	0.548	0.338	0.265	0.259
	SD	0.078	0.13	0.074	0.095
	Min	0.281	0.093	0.1	0.063
	Max	0.733	0.786	0.559	0.615
Median Household Income	Mean	67904	42950	55668	99046
	SD	34751	22248	30615	44268
	Min	5156	2499	4234	11526
	Max	210167	159500	208750	250001
Percent Renter	Mean	52.04	46.16	45.86	57.46
	SD	28.18	22.61	27.74	25.80
	Min	0.00	0.00	0.00	0.00
	Max	100.00	100.00	100.00	100.00
Percent Vacant	Mean	7.46	13.41	10.85	6.84
	SD	6.97	10.67	8.45	6.46
	Min	0.00	0.00	0.00	0.00
	Max	42.98	57.19	57.55	41.01
Percent under 18	Max	51.93	62.98	57.39	44.34
	Mean	19.23	21.63	24.95	13.39
	Min	0.00	0.00	0.00	0.00
	SD	9.80	10.95	9.94	7.42
Population Density (per sq. km.)	Mean	2252	8936	2605	11959
	SD	2074	5580	1898	8625
	Min	0	0	0	0
	Max	19563	57953	15997	65364
Block Group Total Population	Mean	1753	1168	1620	1466
	SD	1166	555	721	687
	Min	0	0	0	0
	Max	10769	4115	5768	9541

Model results

Model results indicated a decrease in crime as the distance to parks increased accounting for covariates. The relationship was significant in all cities for violent crime and in all cities except Phoenix for property crime (see table 4.3).

In the violent crime model, the largest effect was in San Francisco (IRR = 0.34, $p < 0.05$), where being 1 km (approximately a 10 minute walk (Harnik & Martin, 2016)) farther from a park was associated with a 66% decrease in violent crime. The smallest effect of park proximity was in Phoenix (IRR = 0.82, $p < 0.05$), or an 18% decrease in violent crime. Auston and Philadelphia were both associated with a 32% decrease in violent crime (IRR = 0.68 for Austin and IRR = 0.67 for Philadelphia). Park size and NDVI were included in the model, with park size having essentially no association with violent crime amounts. Park NDVI was only significant in Phoenix, where parks with higher NDVI values were associated with an increase in violent crime densities, and San Francisco, where parks with higher NDVI values were associated with decreased violent crime.

In the property crime model, distance to parks was significant in all cities. The largest effect was in San Francisco (IRR = 0.30) indicating that a 1 kilometer increase in distance from a park crime decreases 70%. Phoenix had the smallest effect (IRR = 0.90), associated with a 10% decrease in property crime for a 1 kilometer increase in distance from a park. Park size was significant in Philadelphia, Phoenix, and San Francisco, but at small values. Park greenness was statistically significant only in Phoenix where greener parks were associated with an 8% increase in property crime densities (IRR = 1.08). The non-linear relationship between proximity to parks and crime can be seen in the plots of model predictions (figure 4.3).

Table 4.3a. Model results for violent crime

Violent Crime

Predictors	Austin			Philadelphia			Phoenix			San Francisco		
	Incidence Rate Ratios	*std. Error*	*p*	*Incidence Rate Ratios*	*std. Error*	*p*	*Incidence Rate Ratios*	*std. Error*	*p*	*Incidence Rate Ratios*	*std. Error*	*p*
Intercept	4.15	0.04	**<0.001**	165.78	0.02	**<0.001**	7.80	0.03	**<0.001**	125.58	0.03	**<0.001**
Median household income	0.99	0.00	**<0.001**	0.99	0.00	**<0.001**	0.99	0.00	**<0.001**	1.00	0.00	0.684
% vacant	1.03	0.01	**<0.001**	1.02	0.00	**<0.001**	1.02	0.00	**<0.001**	1.02	0.01	**<0.001**
% renter	1.00	0.00	0.206	1.00	0.00	**<0.001**	1.00	0.00	0.071	1.02	0.00	**<0.001**
Disadvantage index	1.69	0.13	**<0.001**	1.21	0.03	**<0.001**	1.36	0.07	**<0.001**	1.75	0.11	**<0.001**
% under 18	0.99	0.01	0.386	1.00	0.00	0.976	0.98	0.00	**<0.001**	0.99	0.01	0.158
Diversity index	1.11	0.03	**0.001**	0.96	0.01	**<0.001**	1.13	0.02	**<0.001**	1.18	0.03	**<0.001**
Population density (log)	2.21	0.06	**<0.001**	1.57	0.03	**<0.001**	1.83	0.04	**<0.001**	1.47	0.05	**<0.001**
Distance from park (km)	0.68	0.12	**0.001**	0.67	0.08	**<0.001**	0.82	0.06	**0.001**	0.34	0.33	**0.001**
Mean block group NDVI	0.61	0.07	**<0.001**	0.75	0.02	**<0.001**	0.91	0.05	**0.031**	0.68	0.05	**<0.001**
Park NDVI	1.05	0.05	0.320	1.00	0.01	0.960	1.11	0.02	**<0.001**	0.94	0.02	**0.004**
Park size (ac)	1.00	0.00	**0.030**	1.00	0.00	**<0.001**	1.00	0.00	**<0.001**	1.00	0.00	**0.002**
Observations	480			1221			944			554		
Nagelkerke's R^2	0.910			0.919			0.826			0.929		

Table 4.3b. Model results for property crime

Property Crime

	Austin			**Philadelphia**			**Phoenix**			**San Francisco**		
Predictors	*Incidence Rate Ratios*	*std. Error*	*p*	*Incidence Rate Ratios*	*std. Error*	*p*	*Incidence Rate Ratios*	*std. Error*	*p*	*Incidence Rate Ratios*	*std. Error*	*p*
Intercept	53.31	0.03	**<0.001**	187.54	0.01	**<0.001**	62.26	0.02	**<0.001**	422.26	0.03	**<0.001**
Median household income	1.00	0.00	**0.003**	1.00	0.00	**0.773**	0.99	0.00	**<0.001**	1.00	0.00	0.008
% vacant	1.02	0.00	**<0.001**	1.01	0.00	**<0.001**	1.02	0.00	**<0.001**	1.02	0.00	**<0.001**
% renter	1.00	0.00	0.016	1.01	0.00	**<0.001**	1.00	0.00	0.053	1.02	0.00	**<0.001**
Disadvantage index	1.28	0.09	**0.008**	1.00	0.03	**0.884**	1.13	0.06	**0.038**	0.93	0.08	**0.341**
% under 18	0.98	0.00	<0.001	0.99	0.00	<0.001	0.98	0.00	**<0.001**	0.98	0.00	<0.001
Diversity index	0.99	0.02	**0.606**	1.00	0.01	**0.801**	1.08	0.02	**<0.001**	1.04	0.02	**0.068**
Population density (log)	1.86	0.05	**<0.001**	1.26	0.02	**<0.001**	1.75	0.03	**<0.001**	1.24	0.04	**<0.001**
Distance from park (km)	0.74	0.08	**<0.001**	0.76	0.08	**<0.001**	0.90	0.05	**0.032**	0.30	0.25	**<0.001**
Mean block group NDVI	0.59	0.05	**<0.001**	0.71	0.02	**<0.001**	1.05	0.04	**0.169**	0.72	0.04	**<0.001**
Park NDVI	1.05	0.04	0.212	1.00	0.01	0.786	1.08	0.02	**<0.001**	0.97	0.02	**0.071**
Park size (ac)	1.00	0.00	**0.501**	1.00	0.00	**0.004**	1.00	0.00	**<0.001**	1.00	0.00	**<0.001**
Observations			480			1221			944			554
Nagelkerke's R2			0.927			0.859			0.718			0.939

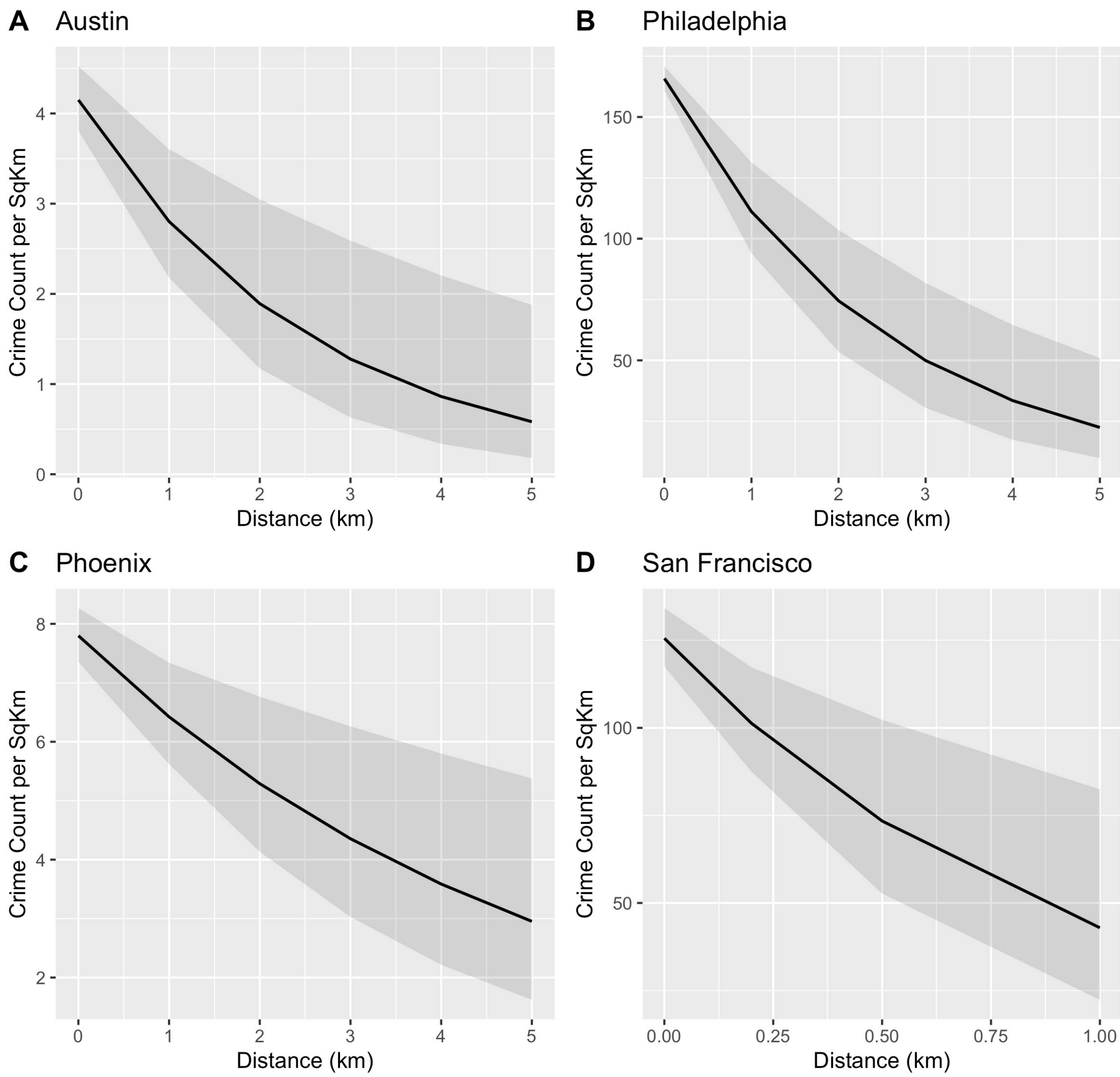

Figure 4.3a. Marginal effects of distance to park on violent crime

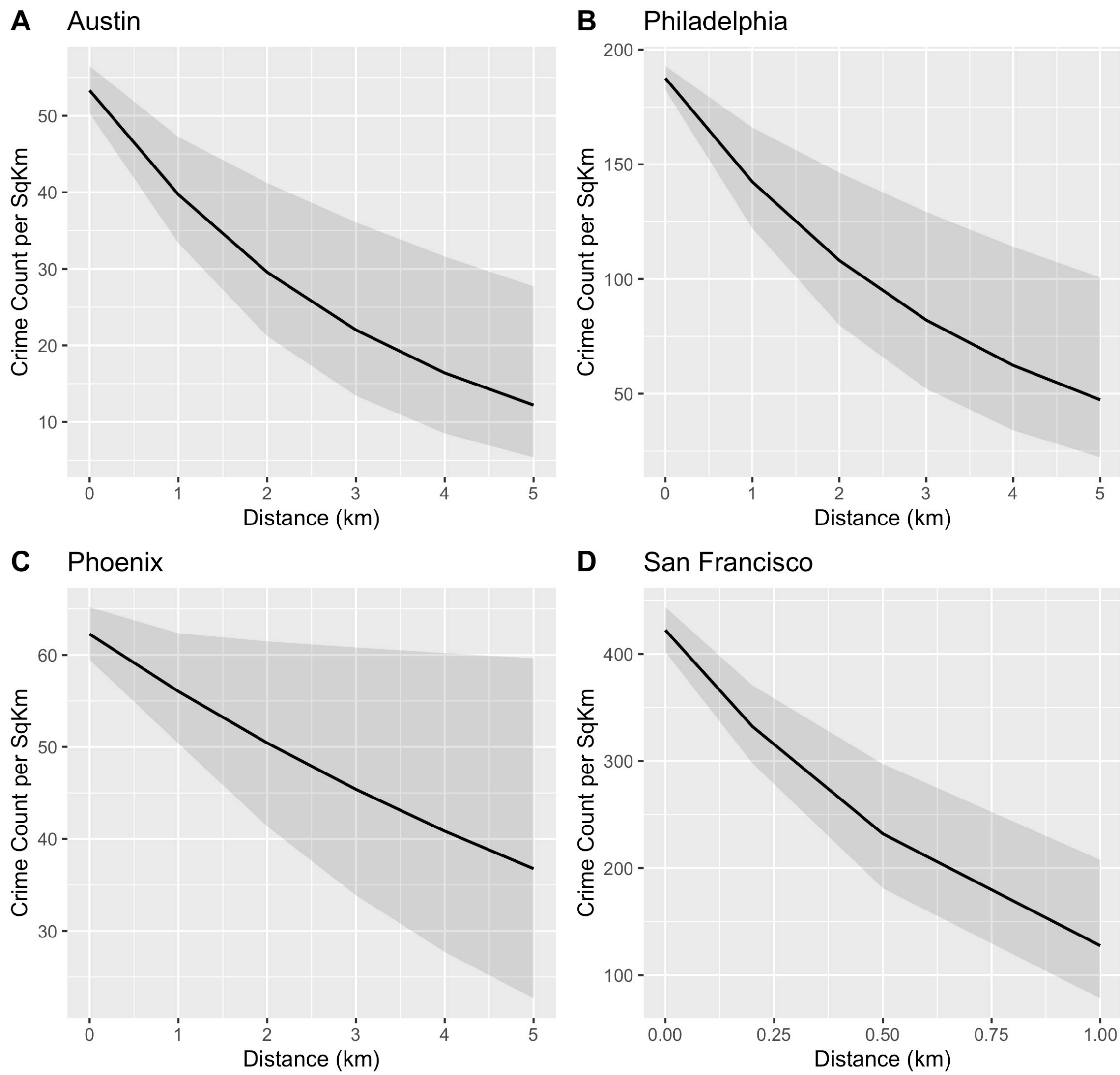

Figure 4.3b. Marginal effects of distance to park on property crime

Discussion

In addressing the question of how proximity to parks and crime are related, we found that in all four cities, when a statistically significant relationship existed, the relationship indicated higher levels of crime closer to parks. As one moves farther from parks, crime densities decrease. This finding is taking into account common covariates of crime and characteristics of the park nearest to a block group, such as park size and greenness.

Finding higher amounts of crime associated with proximity to parks supports prior research that found increased crime close to parks (Boessen & Hipp, 2018; Groff & McCord, 2012; McCord & Houser, 2015). Possible causes for this result can be found in Routine Activities theory, framing urban parks as places where residents make themselves more vulnerable to potential crimes. The activity and common space of parks provides a place for people to come together, and as a side effect, increase the number of targets for property and violent crime (Harp & Karnauskas, 2018).

While disadvantage, income, and diversity are accounted for in the models, it cannot be ruled out that parks may be the victims of their surroundings (Boessen & Hipp, 2018). The location of parks in a city is the result of public and political decisions, from which contemporary perspectives see parks as a tool for the revitalization of neglected sites or underserved communities (De Sousa, 2003; O'Sullivan, 2011). During these transitions the level of crime may remain high due to earlier socioeconomic conditions that existed in a neighborhood (Harris et al., 2017). Additionally, many parks are located to provide benefit to residents in dense residential areas. Though population density was also accounted for in the modeling, areas with greater population are found to have higher crime rates (Nolan, 2004).

Urban parks are often mentioned as an example of greenspace in cities. We included a measure of park greenness, NDVI, in our model to examine how this aspect of parks may influence the relationship to crime. Examining the effect of this variable, we see that in Phoenix and San Francisco park NDVI has a significant relationship with crime. Phoenix has an increasing amount of violent and property crime near greener parks, while San Francisco had a decrease in violent crime with greener parks. Both cities had low NDVI among the case cities and their block groups in general are low in NDVI value compared to parks (see figure 4.4 for Phoenix). It could be that the contrast of green parks to the typically non-green city landscape offers more of an attraction in Phoenix than it would provide in cities that are greener overall, such as Austin or Philadelphia (Jenerette, Harlan, Stefanov, & Martin, 2011). In an arid climate these green parks can attract more people leading to a higher likelihood of being a victim of crime.

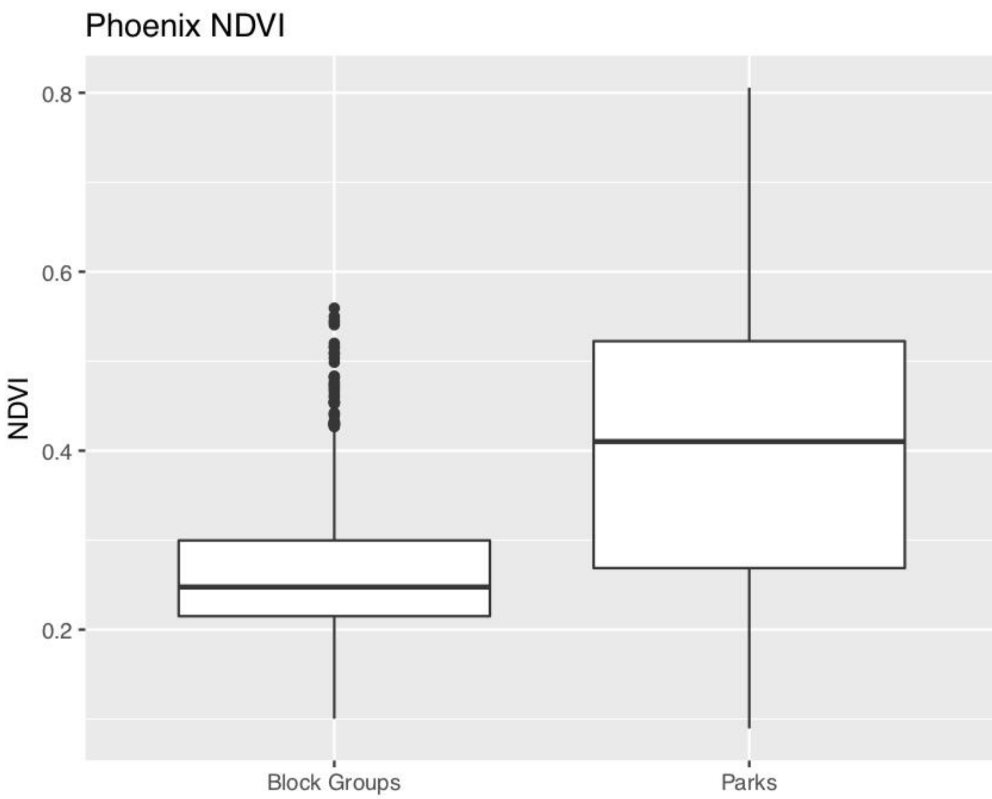

Figure 4.4. Contrast in NDVI between parks and block groups in Phoenix.

Limitations

There are limitations to note within the current research. One common issue with crime data is that it will not include all crimes, as consistency in the reporting of crime varies, leading to the omission of some crimes (Levitt, 1998; MacDonald, 2001; Maltz, 1999; Myers, 1980). The location of crime incidents is typically modified by law enforcement in the name of victim privacy, including the complete censoring of locations or generalization to street blocks. Additionally, error can appear in the socioeconomic variables due to the sampling methodology of the ACS data (Spielman, Folch, & Nagle, 2014). Lastly, data on parks is gathered by the Trust for Public Land, sourced from city agencies which may vary in their ability to provide accurate and current data on parks (The Trust for Public Land, 2019).

Urban parks are not located randomly within cities, but exist as a result of public and political decision-making over many years. Future research can try to capture these processes when investigating how parks influence social and physical conditions. Additional considerations can also include park quality and an assessment of green vegetation beyond what can be determined by NDVI measures.

Conclusion

Urban parks are one intervention that cities can implement to improve the quality-of-life for residents, but their influence on crime should be taken into consideration when locating future park spaces and managing existing ones. Both violent and property crime was found to be higher near parks. Our study shows how this relationship was consistent across cities where typical descriptions of greenspace differ due to climate. The proximity to parks was found to be related to higher crime, but cannot be taken as a cause. The role of parks in the surrounding community, by increasing activity and interaction among people, plays one part in existing theories of crime, such as Routine Activities, where more users equals more opportunities. This negative outcome should be considered in relation to the benefits that arise from parks and greenspace, such as improved public health, social interaction, or environmental conditions (Chiesura, 2004; Dustin et al., 2018; Gobster, 1998; Hartig, Mitchell, de Vries, & Frumkin, 2014).

Urban greenspace is associated with numerous benefits, in contrast this work shows that the type and use of greenspace may be associated with disamenities such as crime. This potential association of parks and crime will require management and planning beyond simply planting vegetation, such as design, maintenance, and programming, to mitigate negative outcomes on communities (D. Cohen et al., 2015, 2010; Lapham et al., 2015). As cities continue to grow, it will be important to ensure that the potential drawbacks of parks are minimized and weighed against the benefits to local residents.

References

Baran, P. K., Tabrizian, P., Zhai, Y., Smith, J. W., & Floyd, M. F. (2018). An exploratory study of perceived safety in a neighborhood park using immersive virtual environments. *Urban Forestry & Urban Greening*, *35*, 72–81.

Beyer, K. M. M., Kaltenbach, A., Szabo, A., Bogar, S., Nieto, F. J., & Malecki, K. M. (2014). Exposure to neighborhood green space and mental health: evidence from the survey of the health of Wisconsin. *International Journal of Environmental Research and Public Health*, *11*(3), 3453–3472.

Blair, L., Wilcox, P., & Eck, J. (2017). Facilities, opportunity, and crime: An exploratory analysis of places in two urban neighborhoods. *Crime Prevention and Community Safety*, *19*(1), 61–81.

Boessen, A., & Hipp, J. R. (2018). Parks as crime inhibitors or generators: Examining parks and the role of their nearby context. *Social Science Research*, *76*, 186–201.

Bogar, S., & Beyer, K. M. (2016). Green Space, Violence, and Crime: A Systematic Review. *Trauma, Violence & Abuse*, *17*(2), 160–171.

Boulton, C., Dedekorkut-Howes, A., & Byrne, J. (2018). Factors shaping urban greenspace provision: A systematic review of the literature. *Landscape and Urban Planning*, *178*, 82–101.

Brantingham, P. L., & Brantingham, P. J. (1995). Criminality of place: Crime generators and crime attractors. *European Journal on Criminal Policy and Research*, *3*(3), 5–26.

Cassal, K. R. (2018). *2018 Esri Diversity Index*. Esri.

Casteel, C., & Peek-Asa, C. (2000). Effectiveness of crime prevention through environmental design (CPTED) in reducing robberies. *American Journal of Preventive Medicine*, *18*(4 Suppl), 99–115.

Ceccato, V. (2014). The nature of rape places. *Journal of Environmental Psychology*, *40*, 97–107.

Chiesura, A. (2004). The role of urban parks for the sustainable city. *Landscape and Urban Planning*, *68*(1), 129–138.

City Parks Alliance. (2019). *Mayors for Parks - City Parks Alliance*. Retrieved https://www.cityparksalliance.org/mayors-for-parks

Cohen, D. A., Han, B., Isacoff, J., Shulaker, B., Williamson, S., Marsh, T., … Bhatia, R. (2015). Impact of park renovations on park use and park-based physical activity. *Journal of Physical Activity & Health*, *12*(2), 289–295.

Cohen, D. A., Inagami, S., & Finch, B. (2008). The built environment and collective efficacy. *Health & Place*, *14*(2), 198–208.

Cohen, D. A., Marsh, T., Williamson, S., Derose, K. P., Martinez, H., Setodji, C., & McKenzie, T. L. (2010). Parks and physical activity: why are some parks used more than others? *Preventive Medicine*, *50 Suppl 1*, S9–S12.

Cohen, L., & Felson, M. (1979). Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review*, *44*(4), 588–608.

Copernicus. (2016). *Sentinel-2 data* [Data set]. Retrieved from https://sentinels.copernicus.eu/web/sentinel/home

Crewe, K. (2001). Linear Parks and Urban Neighbourhoods: A Study of the Crime Impact of the Boston South-west Corridor. *Journal of Urban Design*, *6*(3), 245–264.

Demotto, N., & Davies, C. (2006). A GIS Analysis of the Relationship between Criminal Offenses and Parks in Kansas City, Kansas. *Cartography and Geographic Information Science*, *33*(2), 141–157.

De Sousa, C. A. (2003). Turning brownfields into green space in the City of Toronto. *Landscape and Urban Planning*, *62*(4), 181–198.

Dustin, D., Zajchowski, C., Gatti, E., Bricker, K., Brownlee, M. T. J., & Schwab, K. (2018). Greening Health: The Role of Parks, Recreation, and Tourism in Health Promotion. *Journal of Park and Recreation Administration*, *36*(1), 113–123.

Federal Bureau of Investigation. (2004). *Uniform Crime Reporting Handbook*. Retrieved from https://www2.fbi.gov/ucr/handbook/ucrhandbook04.pdf

Forsyth, A., Musacchio, L., & Fitzgerald, F. (2005). *Designing Small Parks: A Manual for Addressing Social and Ecological Concerns*. John Wiley & Sons.

Gascon, M., Cirach, M., Martínez, D., Dadvand, P., Valentín, A., Plasència, A., & Nieuwenhuijsen, M. J. (2016). Normalized difference vegetation index (NDVI) as a marker of surrounding greenness in epidemiological studies: The case of Barcelona city. *Urban Forestry & Urban Greening*, *19*(Supplement C), 88–94.

Gobster, P. H. (1998). Urban parks as green walls or green magnets? Interracial relations in neighborhood boundary parks. *Landscape and Urban Planning*, *41*(1), 43–55.

Goldstein, B., Dyson, L., & Nemani, A. (2013). *Beyond Transparency: Open Data and the Future of Civic Innovation*. Code for America Press.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18-27.

Groff, E., & McCord, E. S. (2012). The role of neighborhood parks as crime generators. *Security Journal*, *25*(1), 1–24.

Han, B., Cohen, D. A., Derose, K. P., Li, J., & Williamson, S. (2018). Violent Crime and Park Use in Low-Income Urban Neighborhoods. *American Journal of Preventive Medicine*, *54*(3), 352-358.

Harnik, P. (2012). *Urban Green: Innovative Parks for Resurgent Cities*. Island Press.

Harnik, P., & Martin, A. (2016). *Close-to-Home Parks: A Half-Mile or Less*. Retrieved from https://web.archive.org/web/20181003164620/https://parkscore.tpl.org/Methodology/TPL_10MinWalk.pdf

Harp, R. D., & Karnauskas, K. B. (2018). The Influence of Interannual Climate Variability on Regional Violent Crime Rates in the United States. *GeoHealth*, *2*(11), 356–369.

Harris, B., Larson, L., & Ogletree, S. (2017). Different Views From The 606: Examining the Impacts of an Urban Greenway on Crime in Chicago. *Environment and Behavior*, *50*(1), 56–85.

Hartig, T., Mitchell, R., de Vries, S., & Frumkin, H. (2014). Nature and health. *Annual Review of Public Health*, *35*, 207–228.

Hipp, J. R., Kubrin, C., Wo, J., Kim, Y., Contreras, C., Branic, N., … Bates, C. (2016). *Procedures for cleaning, geocoding, and aggregating crime incident data*. Retrieved from http://faculty.sites.uci.edu/ilssc/files/2017/02/geocoding_crime.pdf

Jackson, J., & Stafford, M. (2009). Public health and fear of crime: a prospective cohort study. *The British Journal of Criminology*, *49*(6), 832–847.

Jacobs, J. (1961). *The Death and Life of Great American Cities*. New York, NY: Vintage Books.

Jenerette, G. D., Harlan, S. L., Stefanov, W. L., & Martin, C. A. (2011). Ecosystem services and urban heat riskscape moderation: water, green spaces, and social inequality in Phoenix, USA. *Ecological Applications: A Publication of the Ecological Society of America*, *21*(7), 2637–2651.

Jewell, E. J., & Abate, F. (Eds.). (2001). *The New Oxford American Dictionary*. Oxford University Press New York.

Jones, H., & Vaughan, R. (2010). *Remote sensing of vegetation: principles, techniques, and applications*. Oxford, UK: Oxford University Press.

Jones, K., & Wills, J. (2005). *The Invention of the Park: From the Garden of Eden to Disney's Magic Kingdom*. Cambridge: Polity Press.

Kaczynski, A. T., Potwarka, L. R., & Saelens, B. E. (2008). Association of park size, distance, and features with physical activity in neighborhood parks. *American Journal of Public Health*, *98*(8), 1451–1456.

Keith, S. J., Larson, L. R., Shafer, C. S., Hallo, J. C., & Fernandez, M. (2018). Greenway use and preferences in diverse urban communities: Implications for trail design and management. *Landscape and Urban Planning*, *172*, 47–59.

Kimpton, A., Corcoran, J., & Wickes, R. (2016). Greenspace and Crime. *The Journal of Research in Crime and Delinquency*, *54*(3), 303–337.

Konijnendijk, C. C., Annerstedt, M., Nielsen, A. B., & Maruthaveeran, S. (2013). *Benefits of Urban Parks: A Systematic Review*. Retrieved from http://worldurbanparks.org/images/Newsletters/IfpraBenefitsOfUrbanParks.pdf

Krivo, L. J., Peterson, R. D., & Kuhl, D. C. (2009). Segregation, racial structure, and neighborhood violent crime. *AJS; American Journal of Sociology*, *114*(6), 1765–1802.

Lapham, S. C., Cohen, D. A., Han, B., Williamson, S., Evenson, K. R., McKenzie, T. L., … Ward, P. (2015). How important is perception of safety to park use? A four-city survey. *Urban Studies, 53*(12), 2624–2636.

Levitt, S. D. (1998). The Relationship Between Crime Reporting and Police: Implications for the Use of Uniform Crime Reports. *Journal of Quantitative Criminology*, *14*(1).

MacDonald, Z. (2001). Revisiting the Dark Figure A Microeconometric Analysis of the Under-reporting of Property Crime and Its Implications. *The British Journal of Criminology*, *41*(1), 127–149.

Mair, J. S., & Mair, M. (2003). Violence prevention and control through environmental modifications. *Annual Review of Public Health*, *24*, 209–225.

Maltz, M. (1999). *Bridging Gaps in Police Crime Data* (No. NCJ 176365). Bureau of Justice Statistics.

McCord, E. S., & Houser, K. A. (2015). Neighborhood parks, evidence of guardianship, and crime in two diverse US cities. *Security Journal*, *30*(3), 807-824.

Merriam-Webster Dictionary. (n.d). park. Retrieved from https://www.merriam-webster.com/dictionary/park

Myers, S. L. (1980). Why are Crimes Underreported? What is the Crime Rate? Does it" Really" Matter? *Social Science Quarterly*, *61*(1), 23–43.

Newman, O. (1972). *Defensible space*. Macmillan New York.

Nolan, J. J. (2004). Establishing the statistical relationship between population size and UCR crime rate: Its impact and implications. *Journal of Criminal Justice*, *32*(6), 547–555.

O'Sullivan, E. (2011). *Rejuvenating Neighborhoods and Communities Through Parks—A Guide To Success*. The National Recreation and Park Association.

Ou, J. Y., Levy, J. I., Peters, J. L., Bongiovanni, R., Garcia-Soto, J., Medina, R., & Scammell, M. K. (2016). A Walk in the Park: The Influence of Urban Parks and Community Violence on Physical Activity in Chelsea, MA. *International Journal of Environmental Research and Public Health*, *13*(1).

Pebesma, E. (2018). Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal*. Retrieved from https://journal.r-project.org/archive/2018/RJ-2018-009/index.html

PRISM climate group. (n.d.). *PRISM climate group data* [Data set]. Retrieved from http://prism.oregonstate.edu/

R Core Team. (2017). *R: A language and environment for statistical computing* (Version 3.4). Retrieved from https://www.R-project.org/

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: a multilevel study of collective efficacy. *Science*, *277*(5328), 918–924.

Schusler, T., Weiss, L., Treering, D., & Balderama, E. (2017). Research note: Examining the association between tree canopy, parks and crime in Chicago. *Landscape and Urban Planning, 170*, 309-313.

Shaw, C. R., & McKay, H. D. (1972). *Juvenile Delinquency and Urban Areas*. University of Chicago Press.

Spielman, S. E., Folch, D., & Nagle, N. (2014). Patterns and causes of uncertainty in the American Community Survey. *Applied Geography* , *46*, 147–157.

Stodolska, M., Acevedo, J. C., & Shinew, K. J. (2009). Gangs of Chicago: Perceptions of Crime and its Effect on the Recreation Behavior of Latino Residents in Urban Communities. *Leisure Sciences*, *31*(5), 466–482.

Sugiyama, T., Carver, A., Koohsari, M. J., & Veitch, J. (2018). Advantages of public green spaces in enhancing population health. *Landscape and Urban Planning*, *178*, 12–17.

Sypion-Dutkowska, N., & Leitner, M. (2017). Land Use Influencing the Spatial Distribution of Urban Crime: A Case Study of Szczecin, Poland. *ISPRS International Journal of Geo-Information*, *6*(3), 74.

Taylor, L., & Hochuli, D. F. (2017). Defining greenspace: Multiple uses across multiple disciplines. *Landscape and Urban Planning*, *158*, 25–38.

The Trust for Public Land. (2017). ParkScore Methodology. Retrieved from http://parkscore.tpl.org/methodology.php#sm.0000z78hlgmqrehiwr92pb7oy2a62

The Trust for Public Land. (2019). Parkscore® and Parkserve - About, Methodology, and FAQ. Retrieved https://www.tpl.org/parkserve/about

Tower, S., & Groff, E. (2014). Examining the disorder-crime connection in Philadelphia parks. *Security Journal*, *29*(3).

United Nations. (2015). *Cities - United Nations Sustainable Development Action 2015*. Retrieved from http://www.un.org/sustainabledevelopment/cities/

Vernables, W. N., & Ripley, B. D. (2002). *Modern applied statistics with S*. Springer, New York, New York, USA.

Weier, J., & Herring, D. (2000, August 30). *Measuring vegetation (NDVI & EVI)*. Retrieved https://earthobservatory.nasa.gov/Features/MeasuringVegetation/

Wolfe, M. K., & Mennis, J. (2012). Does vegetation encourage or suppress urban crime? Evidence from Philadelphia, PA. *Landscape and Urban Planning*, *108*(2–4), 112–122.

Younan, D., Tuvblad, C., Li, L., Wu, J., Lurmann, F., Franklin, M., … Chen, J.-C. (2016). Environmental Determinants of Aggression in Adolescents: Role of Urban Neighborhood Greenspace. *Journal of the American Academy of Child and Adolescent Psychiatry*, *55*(7), 591–601.

CHAPTER FIVE

SUMMARY AND CONCLUSIONS

Urban greenspace has gained attention as a means to improve the quality of life for city residents through benefits to mental and physical health, social cohesion, and restoration (Kaczynski, Potwarka, & Saelens, 2008; Kaplan, 1995; Tsai et al., 2018), but disservices such as crime have not been explored in detail. As crime is a serious threat to well-being (Lorenc et al., 2012; Mahuteau & Zhu, 2016), I examined how greenspace and crime are related within a large sample of cities. The relationship showed differences depending on the type of greenspace, but presented a consistent outcome across cities.

My goal was to enrich the understanding of the benefits and drawbacks of greenspace in a community and to fill gaps in the current knowledge. To date research has been isolated to single case studies and used a variety of methods and crime covariates to describe how crime and greenspace are associated. I examined the greenspace and crime relationship through three research questions.

How are crime and greenspace related?

How might greenspace moderate the relationship between temperature and crime?

How is proximity to parks, as a type of greenspace, related to crime?

I have extended the analysis to 301 cities in chapter 2, using the same methodology to understand the direction and strength of association between crime and greenspace. Additionally, in chapter 3 I examined one way that greenspace may influence crime, through its impact on a potential environmental cause of crime – temperature.

Lastly, greenspace is often operationalized as all vegetation, but there are many different types, with urban parks being one type aimed at public use. In chapter 4 the proximity to parks was investigated in four cities to both examine this relationship and compare across differing city contexts.

Findings

The results of chapter 2 pointed to a greater amount of greenspace being associated with less property and violent crime risk. This result held across cities, with only three exceptions for violent crime. These findings support prior research that has pointed to less crime with greener neighborhoods, and extends this result to a large number of cities in the US using a common methodology. This study lends support to including greenspace in city development with crime impacts being one additional benefit for urban residents.

Increasing green vegetation can then be seen as one way to help reduce crime. There is evidence that vegetation has an effect on mood and aggression (Kuo & Sullivan, 2001), which can be a mechanism through which greenspace contributes to reduced crime.

In chapter 3 the study explored how greenspace may impact the relationship between temperature, measured by thermal comfort, and crime. Hotter weather has been found to be related to increases in crime, with extreme heat then leading to decreases in crime. The analysis revealed that as the number of high heat days increased in 2015, crime decreased. Including the interaction between greenspace and thermal comfort revealed that neighborhoods with less greenspace had higher crime but saw a stronger decrease as there were more hot days. Green neighborhoods had less crime and saw little change in crime as there are more hot days.

The ability of greenspace to lower temperatures appears to have the effect of dampening the impact of more hot days on crime. By contributing to a more comfortable environment, greenspace creates conditions that do not reach a point of unbearableness where the only recourse is to seek relief from the heat.

These findings show that including greenspace can be beneficial for residents in reducing the impact of extreme heat and lowering overall crime levels. The effect of extreme heat on reducing crime cannot be seen as a crime reduction method due to the negative effects on well-being and mortality that come from high heat.

In chapter 4 parks, as a subset of greenspace, were found to be associated with higher crime in areas near them. Reasons for this can be found in theories such as Routine Activities, describing crime as the result of targets, lack of guardians, and likely offenders (Cohen & Felson, 1979). Parks are spaces that attract residents and visitors and therefore increase the chance for interpersonal conflict or victimization.

These three studies expand our understanding of how greenspace impacts cities by describing the relationship with crime across a broad sample of cities. Greenspace should be cultivated due to its association with lower crime and ability to make neighborhoods more thermally comfortable, along with benefits to well-being. While green vegetation is found to lower crime, urban parks may lead to increased crime, an outcome that will require management to minimize.

Considering these findings, it is important for residents, planners, and decision-makers to fully understand the impacts of placing greenspace and parks within the city. These landscapes can provide numerous benefits, but can also lead to disservices such as crime, increased costs (Pataki et al., 2011; Shackleton et al., 2016), or gentrification (Cole, Garcia Lamarca, Connolly, & Anguelovski, 2017; Curran & Hamilton, 2012). As more people move to cities it will be key that the greenspace environment be carefully designed and maintained to provide the maximum benefit to local quality of life.

Limitations

While this study sought to describe the crime and greenspace relationship across a broad set of cities, there are some limitations. First, the measurement of greenspace used, NDVI, is a general view of green. Remote sensing provides a large-scale picture of green as vegetation, but does not allow for details to be determined such as accessibility, ownership, or quality. These detailed characteristics could have an influence on how residents perceive greenspace and in how greenspace is used. Second, crime data introduces uncertainty due to modeling in the crime risk index and under reporting or recording errors in the crime incident data. Lastly, this dissertation examined the crime and greenspace relationship at a large scale, across 301 cities or across a whole city, in order to understand broad patterns. This perspective does not allow for local or ground level characteristics to be incorporated.

Further Research

This research points to the relationship greenspace can have with crime in cities. Further research could start to look at specific characteristics of greenspace that are related to crime and other disservices. Many different types of greenspace exist across cities and understanding how these subtypes interact with crime could provide greater understanding of crime and greenspace relationship.

Crime has a distinct spatial pattern and advanced spatial analysis methods could be applied to examine how crime and greenspace are related. Techniques such as geographically weighted regression or point pattern analysis could be used to describe details in how crime and greenspace are related. Additionally, examining the temporal changes in crime could reveal how greenspace influences crime at different times of the day or year.

This dissertation examined how crime and greenspace are related and extended the analysis to a broad sample of cities. The results reveal part of the complex relationship greenspace has with crime. The association of greenspace with reduced crime, and parks with increased crime, illustrates the importance of greenspace in cities but also points to the need to make considered decisions on its placement, design, and care.

References

Cohen, L., & Felson, M. (1979). Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review*, *44*(4), 588–608.

Cole, H. V. S., Garcia Lamarca, M., Connolly, J. J. T., & Anguelovski, I. (2017). Are green cities healthy and equitable? Unpacking the relationship between health, green space and gentrification. *Journal of Epidemiology and Community Health*, *71*(11), 1118–1121.

Curran, W., & Hamilton, T. (2012). Just green enough: contesting environmental gentrification in Greenpoint, Brooklyn. *Local Environment*, *17*(9), 1027–1042.

Kaczynski, A. T., Potwarka, L. R., & Saelens, B. E. (2008). Association of park size, distance, and features with physical activity in neighborhood parks. *American Journal of Public Health*, *98*(8), 1451–1456.

Kaplan, S. (1995). The restorative benefits of nature: Toward an integrative framework. *Journal of Environmental Psychology*, *15*(3), 169–182.

Kuo, F. E., & Sullivan, W. C. (2001). Aggression and violence in the inner city: Effects of environment via mental fatigue. *Environment and Behavior*, *33*(4), 543–571.

Lorenc, T., Clayton, S., Neary, D., Whitehead, M., Petticrew, M., Thomson, H., … Renton, A. (2012). Crime, fear of crime, environment, and mental health and wellbeing: mapping review of theories and causal pathways. *Health & Place*, *18*(4), 757–765.

Mahuteau, S., & Zhu, R. (2016). Crime Victimisation and Subjective Well-Being: Panel Evidence From Australia. *Health Economics*, *25*(11), 1448–1463.

Pataki, D. E., Carreiro, M. M., Cherrier, J., Grulke, N. E., Jennings, V., Pincetl, S., … Zipperer, W. C. (2011). Coupling biogeochemical cycles in urban environments: ecosystem services, green solutions, and misconceptions. *Frontiers in Ecology and the Environment*, *9*(1), 27–36.

Shackleton, C. M., Ruwanza, S., Sinasson Sanni, G. K., Bennett, S., De Lacy, P., Modipa, R., … Thondhlana, G. (2016). Unpacking Pandora's Box: Understanding and Categorising Ecosystem Disservices for Environmental Management and Human Wellbeing. *Ecosystems* , *19*(4), 587–600.

Tsai, W.-L., McHale, M. R., Jennings, V., Marquet, O., Hipp, J. A., Leung, Y.-F., & Floyd, M. F. (2018). Relationships between Characteristics of Urban Green Land Cover and Mental Health in U.S. Metropolitan Areas. *International Journal of Environmental Research and Public Health, 15*(2).

APPENDIX

Appendix A

Cities in Chapter 2 and Chapter 3

Abilene, TX
Akron, OH
Albuquerque, NM
Alexandria, VA
Allentown, PA
Amarillo, TX
Anaheim, CA
Ann Arbor, MI
Antioch, CA
Arlington, TX
Arvada, CO
Athens, GA
Atlanta, GA
Augusta, GA
Aurora, CO
Aurora, IL
Austin, TX
Bakersfield, CA
Baltimore, MD
Baton Rouge, LA
Beaumont, TX
Bellevue, WA
Berkeley, CA
Billings, MT
Birmingham, AL
Boise, ID
Boston, MA
Boulder, CO
Bridgeport, CT
Broken Arrow, OK
Brownsville, TX
Buffalo, NY
Burbank, CA
Cambridge, MA
Cape Coral, FL
Carlsbad, CA
Carrollton, TX
Cary, NC
Cedar Rapids, IA
Centennial, CO
Chandler, AZ
Charleston, SC
Charlotte, NC
Chattanooga, TN
Chesapeake, VA
Chicago, IL
El Monte, CA
El Paso, TX
Elgin, IL
Elizabeth, NJ
Elk Grove, CA
Escondido, CA
Eugene, OR
Evansville, IN
Everett, WA
Fairfield, CA
Fargo, ND
Fayetteville, NC
Fontana, CA
Fort Collins, CO
Fort Lauderdale, FL
Fort Wayne, IN
Fort Worth, TX
Fremont, CA
Fresno, CA
Frisco, TX
Fullerton, CA
Gainesville, FL
Garden Grove, CA
Garland, TX
Gilbert, AZ
Glendale, AZ
Glendale, CA
Grand Prairie, TX
Grand Rapids, MI
Greeley, CO
Green Bay, WI
Greensboro, NC
Gresham, OR
Hampton, VA
Hartford, CT
Hayward, CA
Henderson, NV
Hialeah, FL
High Point, NC
Hillsboro, OR
Hollywood, FL
Houston, TX
Huntington Beach, CA
Huntsville, AL
Independence, MO
Indianapolis, IN
Lowell, MA
Lubbock, TX
Macon, GA
Madison, WI
Manchester, NH
McAllen, TX
McKinney, TX
Memphis, TN
Mesa, AZ
Mesquite, TX
Miami Gardens, FL
Miami, FL
Midland, TX
Milwaukee, WI
Minneapolis, MN
Miramar, FL
Mobile, AL
Modesto, CA
Montgomery, AL
Moreno Valley, CA
Murfreesboro, TN
Murrieta, CA
Naperville, IL
Nashville, TN
New Haven, CT
New Orleans, LA
New York, NY
Newark, NJ
Newport News, VA
Norfolk, VA
Norman, OK
North Charleston, SC
North Las Vegas, NV
Norwalk, CA
Oakland, CA
Oceanside, CA
Odessa, TX
Oklahoma City, OK
Olathe, KS
Omaha, NE
Ontario, CA
Orange, CA
Orlando, FL
Overland Park, KS
Oxnard, CA
Palm Bay, FL
Rochester, NY
Rockford, IL
Roseville, CA
Round Rock, TX
Sacramento, CA
Salem, OR
Salinas, CA
Salt Lake City, UT
San Angelo, TX
San Antonio, TX
San Bernardino, CA
San Diego, CA
San Francisco, CA
San Jose, CA
San Mateo, CA
Sandy Springs, GA
Santa Ana, CA
Santa Clara, CA
Santa Clarita, CA
Santa Maria, CA
Santa Rosa, CA
Savannah, GA
Scottsdale, AZ
Seattle, WA
Shreveport, LA
Simi Valley, CA
Sioux Falls, SD
South Bend, IN
Spokane, WA
Springfield, IL
Springfield, MA
Springfield, MO
St. Louis, MO
St. Paul, MN
St. Petersburg, FL
Stamford, CT
Sterling Heights, MI
Stockton, CA
Sunnyvale, CA
Surprise, AZ
Syracuse, NY
Tacoma, WA
Tallahassee, FL
Tampa, FL
Temecula, CA
Tempe, AZ

Chula Vista, CA
Cincinnati, OH
Clarksville, TN
Clearwater, FL
Cleveland, OH
Clovis, CA
College Station, TX
Colorado Springs, CO
Columbia, MO
Columbia, SC
Columbus, GA
Columbus, OH
Concord, CA
Coral Springs, FL
Corona, CA
Corpus Christi, TX
Costa Mesa, CA
Dallas, TX
Daly City, CA
Davenport, IA
Davie, FL
Dayton, OH
Denton, TX
Denver, CO
Des Moines, IA
Detroit, MI
Downey, CA
Durham, NC
El Cajon, CA
Inglewood, CA
Irvine, CA
Irving, TX
Jackson, MS
Jacksonville, FL
Jersey City, NJ
Joliet, IL
Jurupa Valley, CA
Kansas City, KS
Kansas City, MO
Kent, WA
Killeen, TX
Knoxville, TN
Lafayette, LA
Lakeland, FL
Lakewood, CO
Lancaster, CA
Lansing, MI
Laredo, TX
Las Cruces, NM
Las Vegas, NV
League City, TX
Lewisville, TX
Lexington, KY
Lincoln, NE
Little Rock, AR
Long Beach, CA
Los Angeles, CA
Louisville, KY
Palmdale, CA
Pasadena, CA
Pasadena, TX
Paterson, NJ
Pearland, TX
Pembroke Pines, FL
Peoria, AZ
Peoria, IL
Philadelphia, PA
Phoenix, AZ
Pittsburgh, PA
Plano, TX
Pomona, CA
Pompano Beach, FL
Port St. Lucie, FL
Portland, OR
Providence, RI
Provo, UT
Pueblo, CO
Raleigh, NC
Rancho Cucamonga, CA
Reno, NV
Renton, WA
Rialto, CA
Richardson, TX
Richmond, CA
Richmond, VA
Riverside, CA
Rochester, MN
Thornton, CO
Thousand Oaks, CA
Toledo, OH
Topeka, KS
Torrance, CA
Tucson, AZ
Tulsa, OK
Tyler, TX
Vallejo, CA
Vancouver, WA
Ventura, CA
Victorville, CA
Virginia Beach, VA
Visalia, CA
Vista, CA
Waco, TX
Warren, MI
Washington, DC
Waterbury, CT
West Covina, CA
West Jordan, UT
West Palm Beach, FL
West Valley City, UT
Westminster, CO
Wichita Falls, TX
Wichita, KS
Wilmington, NC
Winston-Salem, NC
Worcester, MA
Yonkers, NY