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The Grass is Always Greener: Analyzing Crime Concentration and Specialization in Urban Greenspace Environs

Cheyenne Hodgen,[a] Kathryn Wuschke[b]

[a] *University of California, Irvine*
[b] *Portland State University*

A B S T R A C T A N D A R T I C L E I N F O R M A T I O N

Greenspaces play an important role in the urban landscape, with prior research suggesting that they are associated with numerous health and social benefits for residents. Despite this, research conflicts regarding the relationship between greenspaces and crime, with some studies finding these locations to be criminogenic and others finding them to be protective against local crime. This study examines this relationship in Portland, Oregon, considering different greenspace types as well as different crime types. Further, this study presents a novel methodological adaption to measure crime concentration and specialization around discrete location types by integrating a street network buffer into the standard Location Quotient (LQ) metric. Results suggest that Portland's greenspaces as a whole do not experience a concentration of crime; however, varying patterns emerge when examining different greenspace and crime types. This study identifies diverse crime concentrations in proximity to small parks, while finding other greenspace categories to be associated with crime-specific concentrations nearby. Others, still, have lower than expected counts of crime concentrating nearby, potentially demonstrating protective trends. These results highlight the importance of disaggregating both crime and location types to better understand the complex relationship between greenspaces and crime.

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Corresponding author: Cheyenne Hodgen, University of California, Irvine, Department of Criminology, Law and Society, 2340 Social Ecology II, Irvine, CA, 92697, USA.
Email: chodgen@uci.edu

Greenspaces play an incredibly important role in urban contexts. Not only do these environments provide space for city residents to experience nature, be active, engage with their community, or relax; they also provide important health and social benefits. These include filtering air toxins, countering the urban heat island effect, strengthening place attachment, and increasing social cohesion (Bowler et al., 2010; Mason, 2010; McCunn & Gifford., 2014; Yang et al., 2005). While these benefits are well-supported in the literature, criminological theories suggest that greenspaces could either promote or prevent criminal activity (Boessen & Hipp, 2018; Groff & McCord, 2011). Thus, the relationship between greenspaces and crime is uncertain. Research reflects this uncertainty, with some studies finding these environments to be associated with higher levels of crime, and others finding the opposite (Boessen & Hipp, 2018; Breetzke et al., 2020; Groff & McCord, 2011; Kimpton et al., 2017; McCord & Houser, 2017; Taylor et al., 2019). Recognizing that the term greenspace refers to many different place types, researchers have pointed to the importance of considering the greenspace type when examining the relationship between these spaces and crime (Eybergen & Andresen, 2022; Kimpton et al., 2017; Shepley et al., 2019).

Understanding the relationship between crime and greenspaces is necessary if we want to preserve these spaces, as well as the benefits they provide. This study aims to examine this relationship in one urban context: Portland, Oregon. By disaggregating greenspace and crime types and using a modified street buffer method to measure crime concentration and specialization, this study aims to further our understanding of the complex relationship between greenspace and crime. If we are able to determine what types of greenspaces are associated with specific categories of crime, we can better target crime reduction efforts to address concerns and reduce crime within and around these important community spaces.

Literature Review

Research concerned with the relationship between crime and place types has its roots in the field of environmental criminology. This group of theories focus on the spatial aspect of crime (i.e., where crimes are occurring) and prioritize understanding the criminal event rather than criminal motivation. One key theory in this field of work is routine activity theory. In its simplest form, routine activity theory posits that crime will (and can only) occur when three elements converge in space and time: a motivated offender, a suitable target, and the absence of a capable guardian (Cohen & Felson, 1979). The geometry of crime approach builds upon this work by introducing several new concepts to further explain why crimes concentrate in certain places and not in others (Brantingham & Brantingham, 1981). The authors posit that the urban environment is broken into subcomponents that help to explain how people use and move through these spaces. Pathways refer to the locations that people use to move through an environment (e.g., roads, paths, rail systems), while nodes refer to the discrete places where people spend a lot of time. Edges refer to physical and perceptual boundaries between areas and can include sharp edges, such as a river, or fuzzy edges, such as gradual land use changes.

The pathways and nodes frequented by an individual make up their activity space, which, along with surrounding areas, makes up the awareness space (Brantingham & Brantingham, 1993). These refer to the areas in which an individual spends most of their time and are therefore familiar with. Major pathways and nodes—those that are part of many individuals' awareness spaces—are therefore more likely to experience higher levels of crime because they offer more opportunities. The Brantinghams term these as crime generators and crime attractors. Crime generators refer to non-residential places that attract a lot of people for non-criminogenic reasons (e.g., shopping malls), which experience an increased number of potential targets and offenders and, as a result, generate more crime (Brantingham & Brantingham, 1995). An attractor, on the other hand, is a place known to be suitable for certain crimes, attracting motivated offenders for that specific reason (Brantingham & Brantingham, 1995). An example would be a specific place (such as a space within a park or a bar) that is known for being a good spot to purchase illegal drugs due to the absence of capable guardians or presence of sellers. All of these features are influenced by their environmental context, or backcloth—which changes over time—highlighting the fluid, temporal aspects of place.

Guided by these environmentally-framed approaches to crime analysis, and the assumption that offenders and targets must converge in space and time, Sherman and colleagues (1989) examined the concentration of predatory crimes in Minneapolis—introducing the idea of crime hot spots. The idea of crime hot spots—places where crime events concentrate—has since found a large amount of support in criminological research (Andresen et al., 2017; Sherman et al., 1989; Weisburd et al., 2004). Sherman and colleagues recognized that the nonrandom distribution of crime could be caused by the nonrandom distribution of people or that certain places—by virtue of their routine activities—could be criminogenic (Sherman et al., 1989). Research on hot spots has generally supported the latter hypothesis, finding certain types of places (e.g., bars, malls, parking lots) to be more criminogenic (Bernasco & Block, 2011; Drawve & Barnum, 2018; Hart & Miethe, 2014). Even within specific place type (e.g., different types of bars), research has identified an uneven distribution of crime. Therefore, exploring disaggregate land use and place type categories can provide us with a better understanding of the specific places that are associated with high levels of crime (Wuschke & Kinney, 2018). A similar argument has been made for disaggregating crime types, as different crime subtypes result from different opportunity structures, and, therefore, the spatial patterns and hotspots of different crime categories will vary (Andresen & Linning, 2012).

Greenspaces and Crime

In the past decade, several studies have examined the relationship between greenspaces and crime in urban environments. The term greenspace refers to areas "synonymous with nature" and encompasses a number of different place types including neighborhood parks, forests, gardens, and vegetated areas (Shepley et al., 2019, p. 5120). Due to the broad nature of the term, studies often attempt to narrow this focus, either by breaking greenspaces up into types based on specific features (such as those with playgrounds) or by focusing solely on one type (such as parks; Breetzke et al., 2020; Groff & McCord, 2011; Kimpton et al., 2017; McCord & Houser, 2017; Taylor et al., 2019).

There is a conflict within criminological theories regarding whether greenspaces act as crime attractors or generators or whether these locations serve to reduce nearby crime. On one hand, greenspaces that draw in a number of legitimate users may experience low levels of crime due to the increased levels of guardianship (Breetzke et al., 2020; Groff & McCord, 2011; Kimpton et al., 2017). In a 2019 evidence synthesis, Shepley and colleagues (2019) concluded that, based on the results of 45 quantitative and qualitative studies, the presence of parks and other greenspaces reduced urban crime. A recent study of the relationship between greenspace and gun violence in Detroit found that greenspaces had a lower density of gun violence, suggesting that residents are not attracted to the unmaintained greenspaces, and due to this low usage, they are unable to function as crime generators (Breetzke et al., 2020).

Other research has contradicted this finding, suggesting that greenspaces can act as crime generators or attractors. Groff and McCord (2011) and McCord and Houser (2017) found evidence of this in their examinations of neighborhood parks in Philadelphia and Louisville, respectively. Both studies found an increased concentration of violent, property, and disorder crime events both in and around park spaces (Groff & McCord, 2011; McCord & Houser, 2017). Groff and McCord determined that parks with a higher number of in-park activity generators (e.g., sports fields) were associated with significantly lower amounts of crime, suggesting that the increased guardianship from legitimate users of the space may deter crime (Breetzke et al., 2020; Groff & McCord, 2011).

Recognizing the impact that the presence of amenities and activity-generators could have on greenspaces, Kimpton and colleagues (2017) examined the relationship between crime and four greenspace types: "amenity rich," "sit or play," "transport," and "amenity poor" (p. 315). Given that greenspaces can be used in various ways, the authors posited that the greenspaces' ability to generate crime may also vary. This was supported by their findings. They found that public nuisance crime occurred disproportionately in "sit and stay" and "transport" greenspaces, the types that would likely be more resistant to outsiders. Additionally, they found that property crime occurred disproportionately in "amenity rich" and "amenity poor" greenspaces, which could be explained by the higher number of available targets (in "amenity rich") or the low number of guardians (in "amenity poor"; Kimpton et al., 2017).

An alternative approach is that greenspaces could act as edges, where "outsiders" are not easily identified, making them places where people may be more comfortable committing crimes due to the anonymity and reduced likelihood of being confronted (Brantingham & Brantingham, 1993). In 2014, Hipp and colleagues (2014) found support for this, finding that parks can function as "social holes," reducing residents' sense of cohesiveness and attachment to their neighborhood. A recent study centered on the Canadian city of London, Ontario, produced results in line with this premise, identifying that while most park types are protective in nature and are associated with lower risks of property crime in surrounding areas, regional parks attract a large crowd of non-local residents and are found to have a positive relationship with property crimes (Eybergen & Andresen, 2022). Thus, current research on greenspaces reflects these theoretical conflicts, with some studies finding that greenspaces are not associated with crime and others finding a strong relationship (Boessen & Hipp, 2018; Breetzke et al., 2020; Eybergen & Andresen, 2022; Groff & McCord, 2011; Kimpton et al., 2017; McCord

& Houser, 2017; Shepley et al., 2019; Taylor et al., 2019).

The research discussed above has greatly improved our understanding of the relationship between greenspaces and crime. These spaces play important roles in the urban environment, providing a local meeting spot with numerous health and social benefits (Bowler et al., 2010; Mason, 2010; McCunn & Gifford, 2014; Yang et al., 2005). In some contexts, they can act as crime attractors or generators, resulting in more crime at and around these locations (Eybergen & Andresen, 2022; Groff & McCord, 2011; McCord & Houser, 2017). In other contexts, they appear to exhibit protective elements (Breetzke et al., 2020; Eybergen & Andresen, 2022). Given the range of greenspace types, as well as the range of different crime types, this relationship may vary according to both location and crime type. By building on existing work and conducting a thorough analysis of multiple greenspace and crime types, we can expand our understanding of these important locations. This growth in understanding is both critical and timely, as such knowledge can facilitate targeted crime prevention initiatives and may inform ongoing policy decisions regarding funding and development, thereby helping to protect these places and the numerous benefits they provide for community residents.

Current Study

There are 318 greenspace locations within the City of Portland, Oregon (Portland Parks and Recreation, 2022a). These include numerous types of greenspaces, such as parks and community gardens. A recent survey of Portland residents reported that 94% of respondents had visited a Portland park at least once in the past 12 months, and roughly 50% reported visiting at least weekly (Portland Parks and Recreation, 2017). Furthermore, in 2014, the city's Parks Replacement Bond was approved, which provides $68 million dollars to make urgent repairs and improvements to Portland greenspaces (Portland Parks and Recreation, 2022b). This Bond is still in progress, making vital improvements to prevent closures of greenspaces in the city. Thus, it is clear that greenspaces are an important element of the urban environment in Portland. Despite this, no studies have examined the local relationship between these locations and crime. Understanding this relationship is both timely and vital to practitioners who continue to make decisions regarding park development and improvements. Further, the results may allow policy makers to prioritize the implementation of preventive measures if greenspaces appear to be criminogenic. Determining which greenspaces, or what type of greenspaces, have a crime problem is a necessary step in ensuring that resources and funding are allocated effectively. Therefore, the goal of this study is to determine whether crime concentrates around greenspaces in Portland and how this may differ by location and crime type. This study seeks to answer three key research questions:

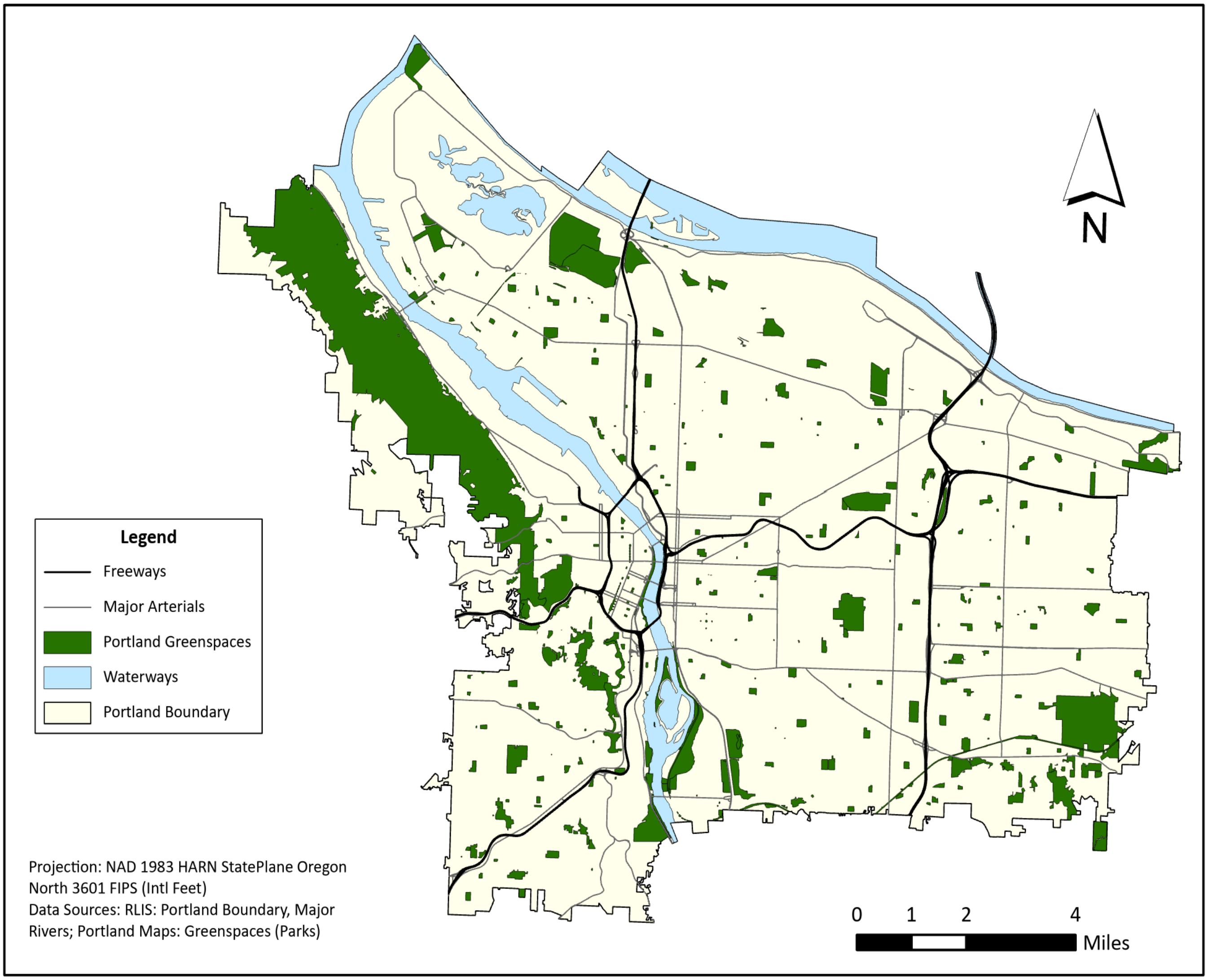
1. Do crime events concentrate in and around greenspaces within Portland?
2. Does the level of concentration vary by crime type?
   a. Do Portland's greenspaces specialize in some crime types?
3. Does the level of concentration vary by greenspace type?
   a. Do different greenspaces specialize in different crime types?

Data and Methodology

Data Preparation

The study area for these analyses is the Portland city limit. Data were obtained from several sources. First, Oregon Metro's Regional Land Information System Portal (RLIS Discovery) was used to obtain spatial files for the city administrative boundaries, major rivers, and the road network (Oregon Metro, 2022). A greenspace shapefile was obtained from the Portland Maps open data portal (PortlandMaps, 2022). The initial greenspace shapefile included 318 locations and provided the location name and size. Three locations were excluded because they fell outside of the city boundary, resulting in 315 discrete greenspaces within the Portland city limits. Portland's greenspaces are dispersed across the city, with over 80% of neighborhoods containing at least one such space. Portland's southeastern region houses the highest count of the city's greenspaces, while the southwestern region (which includes the city center) boasts the highest rate of greenspaces per area. In spite of this variation, greenspaces do not exhibit significant spatial clustering at this spatial level (Global Moran's Index: -0.09; z-score: 0.21, p-value: 0.84, indicating a spatial distribution not significantly different than random). Portland's parks are illustrated in Figure 1.

Figure 1: Spatial Distribution of Greenspaces Across Portland, Oregon (2022)



The Portland Parks and Recreation website was used to collect detailed information on these greenspaces (categorized as park, natural area, arboretum, public garden, rose garden, community garden, community and arts center, community school, memorial, museum, swim pool [indoor], swim pool [outdoor], golf course, raceway, and rental facility; Portland Parks and Recreation, 2022a). For the purpose of this study, the definition of greenspace is any public space that is predominately outdoors and contains vegetation in the form of grass, trees, or gardens. Thus, the study is limited to four greenspace categories, coded as follows: (1) parks, defined as greenspaces set aside for public recreation, sports, or leisure use; (2) natural areas, which are greenspaces that have no official designated purpose, tend to be less maintained, and offer walking/hiking trails; (3) public gardens, which include rose gardens and arboretums, and refer to greenspaces that provide space for residents and visitors to view/experience nature; and (4) community gardens, defined as greenspaces where the primary purpose is to grow and provide produce for community residents (see Table 5 in the appendix for more details). Category 1, parks, are further disaggregated into small parks (smaller or equal to 10 acres) and large parks (larger than 10 acres). This is done to distinguish between smaller neighborhood parks, which have been frequently examined in park-crime studies (Groff & McCord, 2011; McCord & Houser, 2017), and larger parks that may draw in visitors from further away (Eybergen & Andresen, 2022). This information was coded for all locations listed on the Portland Parks and Recreation website (*N* = 317). These attributes were joined to the greenspace shapefile using ArcGIS Pro. Of the 315 discrete areas identified within the greenspace spatial file, 236 were able to be matched with attribute records. Of these, 24 greenspaces were excluded due to size or type, resulting in a final count of 212 locations (see Table 1).

Table 1: Greenspace Locations Included in Analysis

Greenspace Type	*f*	%
Park	151	71.2
Large Park (>10acres)	48	22.6
Small Park (<10acres)	102	48.1
National Area	25	11.8
Public Garden	7	3.3
Community Garden	30	14.2
	212	

Crime event data for 2016 through 2019 were obtained from the Portland Police Bureau's (PPB) open data portal (Portland Police Bureau, 2022). This dataset contains the event type, date of occurrence, time of day, and spatial coordinates aggregated to the nearest intersection or street midpoint. A total of 236,083 events occurred between 2016 and 2019. PPB excludes the case number and address data for any cases deemed sensitive due to the nature of the crime or victim, the victim-offender relationship, or the investigation status (Portland Police Bureau, 2022). Due to this, 26,445 (11.2%) events were excluded. The remaining events were displayed using ArcGIS Pro, and a further 1,022 events were excluded as they fell outside of the city boundary. All remaining crime events (*n* = 208,616) were included in this analysis as an aggregate category (all crime, visualized in Figure 2) and were then broken into the broad subcategories of crimes against persons, property, and society, as defined by the PPB. The three to four highest-volume crime types within each subcategory were also isolated for further analysis, focusing on incidents reported in highest volumes in and near Portland greenspaces.

Methodology

Crime patterns in and around discrete places are frequently measured using location quotients (LQ). The LQ is a simple metric designed to facilitate comparisons of crime across sub-units within an area (Wuschke, Andresen, & Brantingham, 2021). There are two common conceptualizations of the LQ within criminological literature. Adapted from urban and regional planning, the LQ was first introduced to criminology by the Brantinghams as a metric to supplement traditional spatial crime analysis (Brantingham & Brantingham, 1998). Recognizing that crime counts and rates only provide part of the picture, this application of the LQ (which we will refer to as the LQ-Specialization, or the $LQ_{(S)}$) supplements these common measures by identifying relative crime specialization within sub-areas (Andresen et al., 2009; Brantingham & Brantingham, 1998). The ease at which the $LQ_{(S)}$ facilitated between-area comparisons resulted in further modifications and continued applications within criminological literature. These adaptations led to the development and use of what we will refer to as the LQ-Concentration (or the $LQ_{(C)}$), which identifies relative crime concentration within sub-areas (see, for example, Groff & McCord, 2011; Wuschke, Andresen, & Brantingham, 2021). Both the $LQ_{(C)}$ and the $LQ_{(S)}$ provide important insight into local-level spatial crime patterns, with the former highlighting areas that have higher than expected rates of crime, and the latter providing insight into the most common crime type within each sub-unit.

Operationalizing $LQ_{(C)}$ and $LQ_{(S)}$ Measures

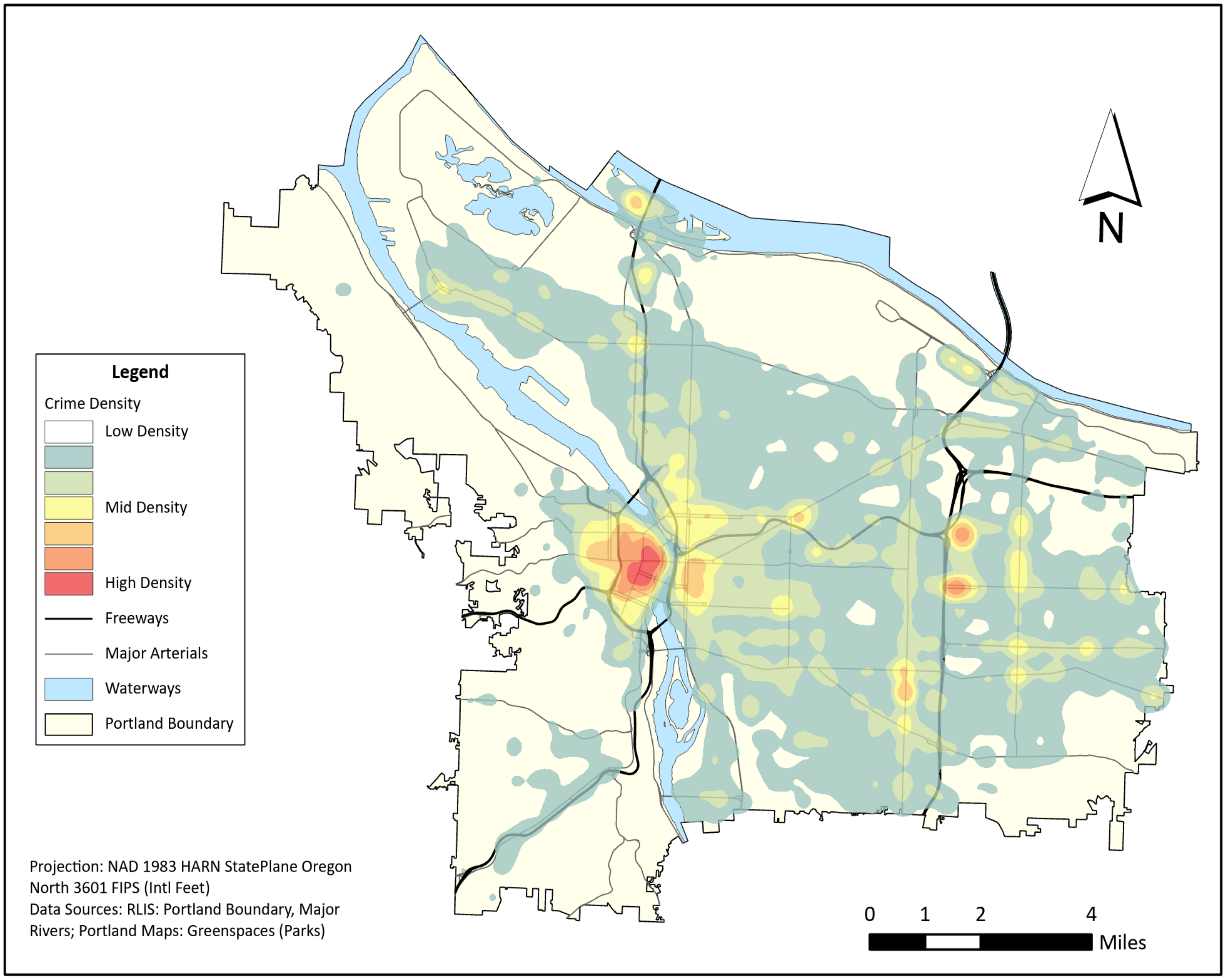
$LQ_{(C)}$ measures can be thought of as a rate ratio, where the crime rate within a subarea is standardized according to crime rates within the study area as a whole. This measure identifies whether and where crime concentrates within these sub-areas (Wuschke, Andresen, & Brantingham, 2021). Within this study, the $LQ_{(C)}$ is calculated as:

$$LQ_{(c)} = \frac{C_e/A_e}{C_a/A_a}$$

Where:
$LQ_{(C)}$ = Location Quotient - Concentration
C_e = Count of crime occurring in sub-area (environ)
A_e = Area of sub-area (environ)
C_a = Count of crime occurring in study area
A_a = Area of study area

In contrast, the $LQ_{(S)}$ metric provides an assessment of the types of crime within a sub-area, determining whether there is more or less of a given crime type than expected based on the patterns exhibited by the larger area as a whole. Thus, $LQ_{(S)}$ measures crime specialization, providing insight into

Figure 2: Density of All Crime Incidences Across Portland, Oregon (2016–2019)



the type of crime most prevalent within a given location – even if the area has relatively low crime counts or concentration overall. Within this study, the $LQ_{(S)}$ is calculated as:

$$LQ_{(s)} = \frac{C_{ie}/C_{te}}{C_{ia}/C_{ta}}$$

Where:
$LQ_{(S)}$ = Location Quotient - Specialization
C_{ie} = Count of crime type i occurring in study sub-area (e, representing environ)
C_{te} = Total count of all crime occurring in sub-area (e, representing environ)
C_{ia} = Total count of crime type i occurring in study area as a whole (a)
C_{ta} = Total count of all crime occurring in study area as a whole (a)

Interpreting $LQ_{(C)}$ and $LQ_{(S)}$ Results

Both $LQ_{(C)}$ and $LQ_{(S)}$ values are interpreted using the same scale. A value of 1.0 means that the level of crime within the sub-area is the same as the overall study area, while a value below 1.0 suggests that the sub-area has lower crime levels, and a value above 1.0 suggests that the sub-area has higher crime levels (Wuschke, Andresen, & Brantingham, 2021). Andresen and colleagues (2009) provide a useful way of categorizing and interpreting LQ values, which has been slightly adapted for the purposes of this study: very underrepresented areas (LQ < 0.5), moderately underrepresented areas (0.5 ≤ LQ < 0.7), slightly underrepresented areas (0.7 ≤ LQ < 0.9), average representation (0.9 ≤ LQ < 1.1), slightly overrepresented areas (1.1 ≤ LQ < 1.3), moderately overrepresented areas (1.3 ≤ LQ < 2.0), and very overrepresented areas (LQ ≥ 2.0; adapted from Andresen et al., 2009). While there is currently no widely-accepted statistical metric to indicate significance, this study considers an LQ of 2.0 to be particularly noteworthy, as this suggests that a given crime type is twice as concentrated (in the case of $LQ_{(C)}$) or specialized (in the context of $LQ_{(S)}$) in the area around greenspaces as compared to the city as a whole (Groff & McCord, 2011; Wuschke, Andresen, & Brantingham, 2021).

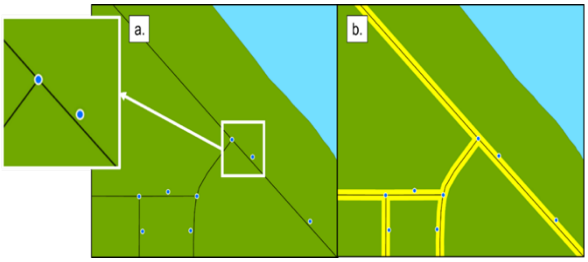
Limits to the LQ Metrics

While both LQ metrics provide a simple and relatively quick way to interpret the level of crime concentration or specialization in an area, there are three limitations worth discussing. First, both variations of the LQ metric are subject to the modifiable area unit problem (MAUP) due to the fact that they measure crime within a sub-area, in comparison to the patterns identified within a wider area. This means that the spatial unit selected for the analysis impacts the results, and must therefore be selected with care (Openshaw, 1984). Being mindful of the importance of these units of analysis, several studies applying the LQ have used Euclidean buffers to create a meaningful sub-area (known as the environ) around a specific location with the goal of capturing nearby (and potentially related) crime events (Groff & McCord, 2011; McCord & Houser, 2017). These measures select all areas within a set distance of the feature of interest (such as greenspaces) and are used to identify crime events that fall within the environ. This can lead to a second limitation: When an LQ calculation relies on area to standardize crime counts (as with the $LQ_{(C)}$), Euclidean buffers can introduce inaccuracies into the measure by including spaces in which crime events are unlikely to occur (such as within waterways, or across impermeable structures). A third limitation relates to the data frequently used within LQ measures. Many police departments (including Portland Police Bureau) aggregate and generalize public crime data to the road network. Crime rate calculations that include area beyond the road network—where crime is not recorded—can further impact the calculation of crime rates by artificially inflating the denominator in calculations of crimes per area.

Alternative approaches to area-based rate measurements (including the $LQ_{(C)}$) have been introduced in recent years, often aiming to calculate a more accurate rate by refining how this standardizing denominator is measured. This has frequently involved excluding locations from the denominator where crimes typically would not occur or where crimes would not be recorded (Ratcliffe, 2012; Wuschke, Andresen, & Brantingham, 2021). Recent adaptations include a modified version of the $LQ_{(C)}$, using the length of the road network as a unit of standardization, rather than the area of the location of interest (Wuschke, Andresen, & Brantingham, 2021). This method excludes all locations that are not typically linked to reported crime incidences, therefore improving the accuracy of the measure of crime incidents per at-risk location. While this helps to address some of the challenges associated with measures of crime concentration, this method is most effective with address-level crime incidents and requires the use of computationally-intensive geoprocessing in order to undertake the network-based analysis. With this in mind, the current study proposes to further refine the spatial unit of analysis forming the structure of both LQ calculations. We present a hybrid methodology that builds on the simplicity and accessibility of Euclidean buffers, while using the road network as the basis for defining both the total study area and the environ sub-areas.

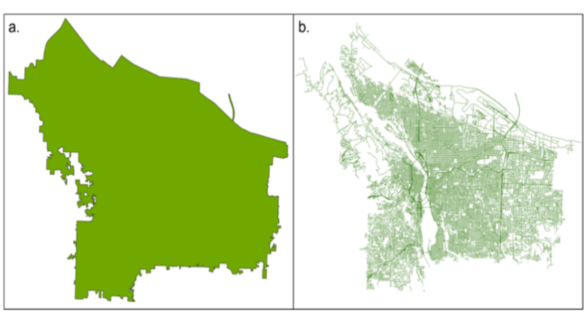
Figure 3 depicts a small sample of crime event locations (represented by blue points) as publicly reported by the Portland Police Bureau (PPB). PPB, like many other organizations, provides aggregate incident locations that are either tied to nearest intersections or are slightly offset from the midpoint of the 100-block centerline. Typical area-based crime rates will calculate the count of incidents per area; however, due to this reporting method, much of the area represented in figure 3a will never have a crime incident associated with it. Regardless of the actual incident location, the points will be generalized to the nearest aggregation point along the road network. This common reporting practice requires us to rethink the use of standard, area-based crime rates and common methods such as traditional Euclidean buffers and $LQ_{(C)}$ measures, as such practices will result in an inflated denominator.

Figure 3: Process of Creating Street Buffers to Capture Aggregated Crime Incidences



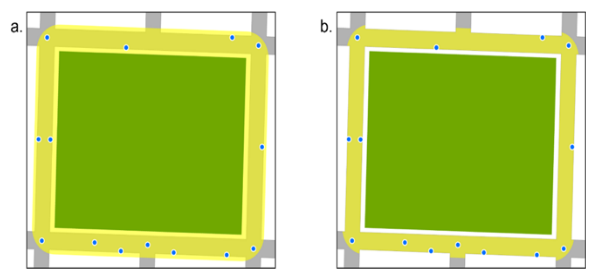
This study addresses this concern through the use of a modified Euclidean buffer to ensure that both the overall study areas are minimized. The street network is used as the input for Euclidean buffers, allowing for the selection of all locations to where crime events may be recorded, while excluding all other areas (displayed in Figure 3b). A buffer distance of 20 feet on each side of the street centerline is used to maximize the selection of crime points included within this analysis, while limiting the total area within the buffers as much as possible. The street network buffer forms the adapted study area and is used to calculate the rate of crimes per area across all of Portland, thus forming the denominator in the $LQ_{(C)}$ calculations (Aa). Shown in figure 4, this reduces the area representing the study site by 86.4%, shrinking the study area from all of Portland (145.3 square miles—shown in figure 4a) to only locations within the street buffer (19.2 square miles—shown in figure 4b), and removing all areas where crime events are typically not recorded.

Figure 4: Process of Reducing Study Area Through the Use of Street Buffers



In addition to the street network base map, additional Euclidean buffers are created around all greenspaces to act as the greenspace environ, which form the subarea within this study (Groff & McCord, 2011). These environ buffers do not include the greenspace itself but measure 60 feet around the perimeter of the greenspace, as this is the minimum distance needed to encompass both sides of all streets and all intersections immediately surrounding the locale (see Figure 5a). This distance was chosen to recognize that incidences happening within the park will be generalized to a neighboring network location and that crime on these bounding streets may be influenced by the presence of the greenspace (Groff & McCord, 2011). While this does not mean that all crime events occurring within the environs are attributable to the greenspace itself, it serves to capture events that occur in or near these important locations and therefore serves as a proxy for greenspace events in the absence of more detailed spatial crime data. The park environ buffer was clipped using our Portland street network base map. This step removes any area that was captured by the environ buffers (the sub-area) but not the street buffer (the study area) and is illustrated in Figure 5b. Clipping the environ to the street buffer ensures that the greenspace environs form a subarea of the larger Portland-wide study site.

Figure 5: Process of Creating (a) and Clipping (b) Greenspace Environs



While the vast majority of crime event data fell within the Portland street network buffers, a small proportion of incidents are located in areas outside of this buffer (1.4%, 2,988). These events are therefore excluded from the analyses. This resulted in a total of 205,628 incidents, which are used as input to create the specific categories used in the analyses: (1) all crime, which includes all incidents recorded by the PPB, and sub-categories, which includes (2) property crimes, (3) person crimes, and (4) society crimes (e.g., public order crimes). Nine discrete crime subtypes are also included: theft from motor vehicles (MV), motor vehicle theft (MVT), vandalism, robbery, simple assault, intimidation, aggravated assault, drug and narcotic violations, and weapon law violations.

Results

RQ 1: Do crime events concentrate in and around greenspaces within Portland?

Between 2016 and 2019, 6,742 criminal incidents (3.3% of all of Portland's reported incidents) occurred within a greenspace environ. With an $LQ_{(C)}$ of 1.2, aggregate level crime (all crime) does not appear to concentrate around local greenspaces and is only slightly overrepresented in greenspace environs compared to Portland as a whole. Breaking this down by crime and greenspace type, however, we see different results.

RQ 2: Does the level of concentration vary by crime type?

Table 2 displays the frequency, $LQ_{(C)}$, and $LQ_{(S)}$ of each crime type within the greenspace environ. Just as all crime events do not concentrate in proximity to the city's greenspaces, this trend continues with the broad crime categories included in this study. This includes property crime, with an average $LQ_{(C)}$ of 1.1, person crime ($LQ_{(C)}$ = 1.7), and society crime ($LQ_{(C)}$ = 1.9). While differences do appear according to broad category, with the $LQ_{(C)}$ of both person and society crimes being moderately overrepresented in areas near greenspaces, the concentration within these environs do not meet the rigorous threshold of 2.0.

However, when disaggregating by crime subtypes, drug and narcotic violations do appear to concentrate in a meaningful way around greenspaces, with an $LQ_{(C)}$ of 2.1. This indicates that drug and narcotic violations are very over-represented and are over twice as concentrated within greenspace environs compared to the city as a whole. Interestingly, motor vehicle theft (MVT) has a $LQ_{(C)}$ of 0.8, suggesting that it is slightly underrepresented around greenspaces. The remaining categories all exhibit slight or moderate concentration in the spaces immediately surrounding greenspaces, though these fail to meet the 2.0 LQ threshold.

RQ 2a: Do Portland's greenspaces specialize in some crime types?

When considering crime specialization surrounding the city's greenspaces, findings echo that of crime concentration within these spaces. While there is variation within the crime distributions within the city's greenspace environs, neither the broad crime categories nor their subtypes reach the $LQ_{(S)}$ threshold to indicate that these offense types specialize within these environs (see Table 2). Property crime, with an $LQ_{(S)}$ of 0.9, displays average representation within greenspace environs, meaning that such events occur within these areas in similar proportions to what we would expect based on the breakdown of crime types within the City of Portland as a whole. Person crimes ($LQ_{(S)}$ = 1.5) and society crimes ($LQ_{(S)}$ = 1.7) are both moderately overrepresented in greenspace environs, meaning that while they do not reach the threshold to indicate notable specialization, these events occur in higher numbers than expected given the overall volume of crime within these spaces.

Table 2: Concentration and Specialization of Crime at and Near Portland Greenspaces

Crime Type	Total	Environ	$LQ_{(C)}$	$LQ_{S(S)}$
All Crime	205,628	6,742	1.2	–
Property Crime	179,707	5,424	1.1	0.9
Theft from MV	39,569	1,474	1.3	1.1
MVT	25,310	568	0.8	0.7
Vandalism	22,465	835	1.3	1.1
Robbery	3,657	168	1.6	1.4
Person Crime	16,481	806	1.7	1.5
Simple Assault	8,601	424	1.7	1.5
Intimidation	3,279	142	1.5	1.3
Aggravated Assault	4,591	240	1.8	1.6
Society Crime	9,440	512	1.9	1.7
Drug/Narc Violations	6,548	385	**2.1**	1.8
Weapon Law Violations	2,007	109	1.9	1.7

Note: MV = Motor Vehicle; MVT = Motor Vehicle Theft. **Bolded** LQ values (both LQ_C and LQ_S) are those that reach or exceed the 2.0 threshold indicating very overrepresented patterns are displayed in bold text.

RQ 3: Does the level of concentration vary by greenspace type?

Next, the concentration of aggregate crime (all crime) is assessed across different greenspace types (as seen in Table 3). Specifically, parks account for 86.0% (5,799) of the total crimes occurring in greenspace environs within Portland (*n* = 6,742). There continues to be variation in the levels of crime concentration, with natural areas ($LQ_{(C)}$ = 0.4), community gardens ($LQ_{(C)}$ = 0.8), and large parks ($LQ_{(C)}$ = 0.9) all having $LQ_{(C)}$ values below 1, suggesting that crime is either moderately or slightly underrepresented around these spaces. Both public gardens and the broad park category (large and small parks combined) display moderately overrepresented $LQ_{(C)}$ values (1.4 and 1.5, respectively). When disaggregating parks into size-based categories, small parks display a meaningful concentration of aggregate

Table 3: Concentration of Total Crime ($LQ_{(c)}$) by Type of Greenspace

Greenspace Type	Number of Crime Incidents	$LQ_{C(C)}$	% of Greenspace Crime (*n* = 6,742)
Community Garden	113	0.8	1.7
Public Garden	291	1.4	4.3
Natural Area	645	0.4	9.6
Park	5,799	1.5	86.0
Large Park	2,011	0.9	29.8
Small Park	3,781	**2.1**	56.1

Note: Bolded LQ values are those that reach the 2.0 threshold, indicating very overrepresented concentration.

crime, with a very overrepresented $LQ_{(C)}$ of 2.1. Small parks account for 56.1% (3,781) of all crime occurring in greenspace environs, followed by large parks (29.8%).

Next, the relationship between different crime types and different greenspace types are examined together. Here, a number of interesting relationships emerge (displayed in Table 4). When considering community gardens, intimidation offenses appear very overrepresented, with a $LQ_{(C)}$ of 3.0. There is, however, only a small number of incidents near these locations, with 7 occurrences between 2016 and 2019. This high value is therefore most likely associated with an inflated rate metric, as a small number of occurrences concentrated in a small area can produce a relatively large incident rate. Shifting focus to public gardens, aggregated society crimes ($LQ_{(C)}$ = 5.3), as well as the subtypes of theft from motor vehicles ($LQ_{(C)}$ = 2.5), drug and narcotic violations ($LQ_{(C)}$ = 7.1), and weapon law violations ($LQ_{(C)}$ = 2.0) all appear to be very overrepresented in the environ. Again, a small crime count for weapon law violations is seen in this area and is important to note when using an $LQ_{(C)}$ metric. Looking at environs surrounding natural areas, no crime type appears to concentrate in the environ. In fact, no crime type has a $LQ_{(C)}$ above 1.0, suggesting that crime is underrepresented in these environs compared to the rest of the city.

When exploring all greenspaces defined as parks (large and small combined), the broad crime categories of person crime ($LQ_{(C)}$ = 2.3) and society crime ($LQ_{(C)}$ = 2.4) are very overrepresented within these areas, as well as the subtypes of robbery ($LQ_{(C)}$ = 2.2), simple assault ($LQ_{(C)}$ = 2.3), aggravated assault ($LQ_{(C)}$ = 2.5), drug and narcotic violations ($LQ_{(C)}$ = 2.5), and weapon law violations ($LQ_{(C)}$ = 2.5). When parks are broken up into categories of large and small, however, large parks do not appear to experience this level of overrepresentation, as no $LQ_{(C)}$ values fall above 2.0. On the other hand, small parks are very overrepresented in almost all broad categories (and sub-types) of crime. Only two crime measures fall below the 2.0 threshold within this environ: the aggregated property crime category, found to be moderately overrepresented ($LQ_{(C)}$ = 1.8), and motor vehicle theft ($LQ_{(C)}$ = 1.1), found to be slightly overrepresented. There is, however, still variation in both the count of different crime types within these environs, as well as the intensity of the concentration.

RQ 3a: Do different greenspaces specialize in different crime types?

When considering crime specialization around different types of greenspaces, the findings again echo that of crime concentration. Focusing first on community gardens, intimidation incidences are very overrepresented, with an $LQ_{(S)}$ of 3.9. While all remaining crime categories and sub-categories fail to meet the threshold to indicate notable specialization within this environ, variation does exist within these categories, typically in alignment with the general trends identified when measuring concentration within these spaces. In public garden environs, society crime ($LQ_{(S)}$ = 3.8) and specifically, drug and narcotic violations ($LQ_{(S)}$ = 5.1) are very overrepresented and therefore specialize within these locales. Within the city's natural area environs, we find no crime type specialization, as measured by $LQ_{(S)}$ values exceeding 2.0. In spite of this, there are some interesting and unexpected patterns in the breakdowns of crime incidents within natural area environs, highlighting the unique value of the $LQ_{(S)}$ measure. For example, while crime concentration in natural areas is consistently underrepresented, indicating lower than expected volumes of crime within these areas, the proportion of those incidents categorized as property, person, and society crime align with what we would expect based on Portland's patterns as a whole. Further, specific sub-categories of crimes stand out as moderately overrepresented within this greenspace environ (theft from motor vehicles [$LQ_{(S)}$ = 1.5] and weapon law violations [$LQ_{(S)}$ = 1.3]). This indicates that while the general risk of crime is lower within the city's natural area environs, the relative risk of both theft from motor vehicle and weapons law violations is higher within these spaces.

When exploring greenspace environs classified as parks, crime specialization findings generally align with overall concentration measures. While no crime category or sub-category meets the

Table 4: Concentration and Specialization of Crime Types Around Different Greenspace Types

	Community Garden *f* (LQ_C; LQ_S)	Public Garden *f* (LQ_C; LQ_S)	Natural Area *f* (LQ_C; LQ_S)	Park *f* (LQ_C; LQ_S)	Large Park *f* (LQ_C; LQ_S)	Small Park *f* (LQ_C; LQ_S)
All Crime	113 (0.8; –)	291 (1.4; –)	645 (0.4; –)	5,799 (1.5; –)	2,011 (0.9; –)	3,781 (2.1; –)
Property Crime	95 (0.7; 1.0)	221 (1.2; 0.9)	565 (0.4; 1.0)	4,631 (1.3; 1.0)	1,723 (0.9; 1.0)	2,905 (1.8; 1.0)
Theft from MV	30 (1.1; 1.4)	99 (**2.5**; 1.8)	191 (0.6; 1.5)	1,189 (1.5; 1.2)	408 (1.0; 1.1)	780 (**2.2**; 1.2)
MVT	12 (0.7; 0.9)	29 (1.1; 0.8)	48 (0.2; 0.6)	493 (1.0; 0.8)	239 (0.9; 1.0)	252 (1.1; 0.6)
Vandalism	20 (1.2; 1.6)	32 (1.4; 1.0)	67 (0.4; 0.9)	723 (1.7; 1.2)	255 (1.1; 1.2)	468 (**2.3**; 1.3)
Robbery	3 (1.1; 1.5)	3 (0.8; 0.6)	6 (0.2; 0.5)	159 (**2.2**; 1.7)	41 (1.1; 1.2)	118 (**3.6**; **2.0**)
Person Crime	16 (1.3; 1.8)	19 (1.1; 0.8)	52 (0.4; 1.0)	730 (**2.3**; 1.7)	183 (1.1; 1.2)	546 (**3.7**; **2.0**)
Simple Assault	5 (0.8; 1.1)	11 (1.3; 0.9)	24 (0.3; 0.9)	388 (**2.3**; 1.8)	78 (0.9; 0.9)	310 (**4.1**; **2.2**)
Intimidation	7 (**3.0**; **3.9**)	4 (1.2; 0.9)	12 (0.5; 1.2)	122 (1.9; 1.4)	27 (0.8; 0.9)	95 (**3.3**; 1.8)
Aggravated Assault	4 (1.2; 1.6)	4 (0.9; 0.6)	16 (0.4; 1.1)	220 (**2.5**; 1.9)	78 (1.6; 1.8)	141 (**3.5**; 1.9)
Society Crime	2 (0.3; 0.4)	51 (**5.3**; **3.8**)	28 (0.4; 0.9)	438 (**2.4**; 1.8)	105 (1.1; 1.2)	330 (**3.9**; **2.2**)
Drug/Narc Violations	2 (0.4; 0.6)	47 (**7.1**; **5.1**)	20 (0.4; 1.0)	321 (**2.5**; 1.9)	70 (1.0; 1.1)	249 (**4.3**; **2.4**)
Weapon Law Violations	0 (0.0; 0.0)	4 (**2.0**; 1.4)	8 (0.5; 1.3)	99 (**2.5**; 1.9)	30 (1.4; 1.6)	68 (**3.8**; **2.1**)

Note: MV = Motor Vehicle; MVT = Motor Vehicle Theft. **Bolded** LQ values (both LQ_C and LQ_S) are those that reach the 2.0 threshold.

$LQ_{(S)}$ threshold of 2.0 within parks in general, all categories that are very over-represented in concentration are also moderately over-represented in specialization. In addition, when isolating large park environs from this category, we continue to see this alignment between concentration and specialization, with most categories occurring in expected volumes and proportions based on city-wide trends. When isolating small parks, however, it becomes clear that these locations are important influences upon the general crime patterns within the city's park environs. Several crime categories appear to specialize in these environs, as both person and society crime are very overrepresented ($LQ_{(S)}$ = 2.0 and 2.2, respectively). Looking at specific crime types, robbery, simple assault, drug and narcotic violations, and weapon law violations are all very overrepresented, indicating that these crime sub-categories, in particular, specialize within small park environs.

Discussion

The relationship between greenspaces and crime is important to understand, given the positive and necessary role they play in the urban environment. In Portland, Oregon, in particular, these spaces form an essential activity node within the lives of urban residents, with the vast majority of residents interacting with these spaces as part of their regular routines (Portland Parks and Recreation, 2017). This study aimed to further examine the relationship between greenspaces and crime in Portland, using a novel spatial methodology that minimizes the study area to facilitate a more stringent representation of this space. The first research question that this study sought to explore is whether crime, in general, concentrates around Portland greenspaces. The results suggest that, overall, crime does not concentrate in and around these important spaces and is only slightly overrepresented within these environs. This is in line with the findings of Breetzke and colleagues (2020) who noted that the presence of greenspaces was not associated with gun violence in Detroit.

Once crime is broken down into more discrete categories, however, we see different levels of both concentration and specialization within Portland's greenspace environs. The aggregate crime categories (all crime, property crime, person crime, and society crime) do not appear to concentrate or specialize around greenspaces. However, when looking at the discrete crime types, levels of crime concentration range from slightly underrepresented, with an $LQ_{(C)}$ of 0.8 (motor vehicle theft), to very overrepresented, with an $LQ_{(C)}$ of 2.1 (drug and narcotic violations). Likewise, crime sub-categories also specialize in different ways within the city's greenspace environs. While no single crime category or sub-type reports an $LQ_{(S)}$ value of very overrepresented within greenspace environs, all measured person and society crime subtypes fall within the moderately over-represented ranges. This means that, given the overall breakdown of crime incidents occurring within greenspace environs, we see moderately higher proportions of person and society crimes than we would expect based on the associated trends exhibited across the city as a whole. These variations in both concentration and specialization reinforce the central argument of Andresen and Linning (2012) who emphasize the importance of disaggregating crime types.

The variation in the concentration and specialization of different crime types suggest that while greenspaces may provide opportunities for certain crimes (i.e., drug and narcotic violations), they may not provide many opportunities for others (i.e., motor vehicle theft). This may be due to the nature of greenspaces as locations where people congregate. As public spaces, they provide a place for people to participate in various activities—both legal and illegal. Thus, it may be the case that we see a notable concentration of drug and narcotic violations because of the openness and inclusivity of this broad land use category, allowing these spaces to act as edges where a variety of users can converge without seeming out-of-place. On the other hand, we see a lower than expected concentration and specialization of motor vehicle thefts within greenspace environs. This could be because during the daytime, the people using the parks act as guardians (preventing the theft of their motor vehicles), while during the evening and nighttime, the absence of people also means that there are fewer targets (in this case, motor vehicles) and therefore fewer opportunities for this crime type to take place (Eybergen & Andresen, 2022).

Just as we found further insight by disaggregating crime categories, disaggregating greenspaces also reveals differing levels of crime concentration. This suggests that different types of greenspaces have different relationships with crime. This study emphasizes that crime as an aggregate category concentrates around and is very overrepresented within the environs of small parks—a finding that is consistent with prior studies focusing on this land use category (Groff & McCord, 2011; McCord & Houser, 2017). In contrast, the city's natural areas, community gardens, public gardens, and large parks each do not meet the 2.0 $LQ_{(C)}$ threshold when measuring aggregate crime concentration within their respective environs. The latter greenspace types do not experience a notable concentration of crime—in fact, most of these environ subtypes report average or lower concentrations than expected as compared to the rest of the city. This variation across greenspace types aligns with expectations based on fundamental differences in how these spaces are used within their respective communities.

We can gain further insight into the nuanced differences in use and associated risk within these spaces by breaking down each greenspace type according to their unique crime profiles. All greenspace types—with the exception of natural areas and large parks—experience a notable concentration of at least one crime type. Findings regarding crime specialization follow suit – areas with high concentrations of a specific crime type frequently (though not uniformly) also report a high degree of specialization within that category. For example, theft from motor vehicles are notably concentrated in the environs of public gardens and are also moderately over-represented within these locales in regards to specialization ($LQ_{(C)} = 2.5$, $LQ_{(S)} = 1.8$). This indicates that there is a higher volume of theft from motor vehicle events within public garden environs than compared to other greenspace types and as compared to patterns exhibited across the city as a whole. Likewise, there is also a moderately higher proportion of theft from motor vehicle events, as a subset of the overall crime mix found within these environs.

To understand why public garden environs, specifically, provide opportunities for theft from motor vehicles in higher rates and proportions than other greenspace environs, we must consider the way these spaces are used. These locations act as destinations within the urban landscape, drawing in a variety of visitors from farther away, who have to leave their vehicles unattended while enjoying the greenspaces. This results in more targets for motivated offenders within these spaces. In contrast, these locations may not experience a concentration of other types of property or person crimes because they provide greater access control within the garden itself (often as a result of admission fees). This element of guardianship in areas beyond the parking spaces may lead to a lower volume and reduced opportunity to specialize in these crime types.

In contrast, public garden environs also exhibit notable concentration and specialization in society crimes, as well as their subcategories. These concentrations are harder to explain – guardianship elements that reduce the volume of most categories of property and person crimes should, in theory, act as protective measures that extend to prevent society crimes as well. This finding may be more related to the space in which the public gardens exist, rather than the gardens themselves (Eybergen & Andresen, 2022). Remembering that the environs are formed as a network-based buffer capturing roads surrounding the greenspaces themselves, this serves to capture crime incidents that may have occurred within the greenspaces but are mapped to the nearby road network surrounding the space. However, this environ also captures events that are naturally occurring on the edges between these greenspaces and their surrounding neighborhoods – edges where we may expect crime to concentrate based on their very nature as connecting spaces between environmental zones (Brantingham & Brantingham, 1993). While the crime data used within this study does not allow us to distinguish between the specific environmental feature on which the event occurs, further research considering surrounding land uses can be useful to identify whether crime concentrations and specialization are more likely to be aligned with the greenspace or the surrounding milieu.

A key finding of this research emphasizes the importance of small parks as important features within Portland's urban landscape. These environs experience concentration across all but one discrete crime category: motor vehicle theft. Because small parks are designed to serve their surrounding communities, they are likely located in largely residential areas (compared to public gardens, natural areas, and large parks). As a result, they may be frequented more often by neighborhood residents and visitors. This could suggest an increased level of guardianship—which should be associated with lower concentrations of crime—or it could suggest a higher number of targets—which would be associated with higher concentrations of crime (Groff & McCord, 2011). The latter assumption is supported by these findings, as small park environs experience a concentration of all person and society crime types. When considering specialization, similar findings emerge. Of the proportion of crimes recorded within small park environs, we see person and society categories, as well as sub-crime types as moderately or very over-represented. This indicates that these crimes occur in both high volumes and in higher proportions within small park environs than we would expect based on trends within other greenspace environs or within the city of Portland as a whole. This finding is interesting and may indicate that these urban features act as crime attractors and/or generators within their respective communities, drawing in opportunities for interactions within these local meeting spaces. In order to further understand the mechanisms behind these concentrations, a temporal analysis of crime in and around greenspaces will help to further illuminate this relationship between how the presence of people relates to crime at these locations.

Overall, the findings of this study suggest that different greenspace types provide different opportunities for different crimes. This finding is consistent with the work of Wuschke and Kinney (2018) who argue that breaking down land use categories can help us gain a clearer understand of the specific relationships between crime and place (Wuschke & Kinney, 2018). These findings also echo the work of Eybergen and Andresen (2022), who identify important differences in surrounding crime based on park category.

These findings have important implications for both policy-makers and practitioners. Most notably, these results emphasize that crime prevention strategies should be designed to be both place- and crime-specific. For example, small parks in Portland experience a higher-than-expected concentration of crime, and specialize robbery, as well as person and society crimes. Likewise, other greenspace types exhibit crime-specific concentrations and specializations unique to these facilities. Therefore, crime prevention strategies should be designed with these specific spaces in mind. The ongoing Park Replacement Bond may present an opportunity to do so by allocating funds to further examine and address these crime concerns. Beyond Portland, these findings offer support to existing research emphasizing the varied relationship between greenspaces and crime and stress the importance of conducting local analyses to understand the nuanced and dynamic relationship between these features within urban spaces (Eybergen & Andresen, 2022; Kimpton et al., 2017).

In addition to the practical local findings presented within this study, the methodological adaptations incorporated within this research show promise in wider spatial applications. By limiting the study area to a small zone surrounding the city's street segments, areas where crime is unlikely to occur, or unlikely to be recorded on, are removed from the analysis. Removing these spaces helps to avoid rate inflation, which is a common concern with rate-based measures and is a common limitation in studies employing the $LQ_{(C)}$ metric (Wuschke, Andresen, & Brantingham, 2021). When calculating crimes per area, a large denominator (such as the area of the entire city) falsely reduces the overall city-wide rate of crime. As a rate ratio, the $LQ_{(C)}$ then compares the relatively low city-wide measure to related calculations of crime within smaller sub-locales. Even small counts of crime in these sub areas can appear meaningful as a result. By removing all areas where the PPB does not record criminal events, the impact of a large denominator is minimized, thus strengthening the measure of the $LQ_{(C)}$ without negatively impacting the calculations related to the $LQ_{(S)}$. This method is designed to accommodate crime data that have been offset from the street network or generalized to block midpoints and intersections. As more police departments begin to provide public access to crime data, methods to best represent and measure patterns using these public sources become ever more important (Wuschke, Henning, & Stewart, 2021). The crime data publicly available from the Portland Police Bureau are similar to that provided by other agencies in that they aggregate crime points in an effort to anonymize the data. Thus, developing meaningful ways to measure crime concentration using data that are publicly accessible is critical for continued research exploring spatial patterns of crime.

Limitations and Future Direction

While both methods and findings of this study contribute to the existing academic literature exploring greenspaces and crime, there are several limitations that warrant attention within future research. First, this study employs two versions of the Location Quotient as measures for both concentration and specialization. While the $LQ_{(C)}$ and $LQ_{(S)}$ both offer powerful and easy-to-understand measures of concentration and specialization, respectively, around locations of interests, there are still limitations associated with these measures. Like most rate-based measures, both variations of the LQ are subject to rate inflation, as is seen in several instances where the crime count is low, but the small area, or small count of total crime within this area, resulted in a meaningfully high LQ. While providing two LQ measures strengthens this analysis by providing a further lens with which to consider these relationships, it is important to interpret the results of this study while being mindful of the count of crime and LQ values (Brantingham & Brantingham, 1998; Wuschke, Andresen, & Brantingham, 2021).

In addition, the street network buffer method used in this study is quick, relatively computationally light, and allows for a considerable reduction in area measures used within this study. However, the buffers themselves are still Euclidean in design, selecting all areas within 20 feet of a roadway. This means that they may falsely make connections between two nearby streets, even if these areas are not physically connected. Further, the park environs are also Euclidean in nature. When clipped to the street buffer, these environs may still capture and include area that may not be physically connected to the park (such as a dead-end street that falls within the 60-foot environ area). For the purposes of this study, the lack of physical connectivity via road networks is likely to be minimally impactful, as there are countless informal paths that connect dead-end roads to other nearby routes. In areas or studies where accurate topographic connections are critical, network-based analysis would offer a more topographically accurate approach (Wuschke, Andresen, & Brantingham, 2021). However, the simplicity and accessibility of the hybrid design, incorporating street networks while using widely-available spatial tools, make this a useful addition to the spatial analytical toolkits of a wide range of users.

This study focused on determining whether crime (and different crime types) concentrates around different greenspace types in Portland, Oregon. While this is an important contribution and necessary precursor to further studies of parks and crime in Portland, it is exploratory in nature. As such, it raised a number of interesting research directions, providing a number of avenues for further consideration. Future research can continue to explore this topic by considering the influence of different amenities present at greenspaces, as well as how these amenities may shift the overall usage of the park at different times of day (e.g., sports courts, public transit, guided by the work of Groff and McCord, 2011, and McCord and Houser, 2017). In addition, considering the impact of other neighborhood characteristics (such as poverty levels and social disadvantage) will continue to be an area to explore (Boessen & Hipp, 2018; Eybergen & Andresen, 2022). Incorporating both temporal and spatial analytical elements will serve to identify both where and when parks may act as protective features or as attractors or generators of crime. Indeed, such research may identify whether the same location may switch between these roles throughout the day. Further research opportunities should also investigate the impact of land use near the parks themselves as well as crime patterns within the areas beyond the parks in order to provide further depth to the understanding of events in and around these important urban focal points.

Conclusion

This study aimed to understand the relationship between greenspaces and crime in Portland, Oregon, using an adapted street network buffer to measure the concentration and specialization of crime around greenspaces. This proposed method offers a stringent yet simplified way to measure crime concentration and specialization using publicly available, aggregated crime data, along with simple geospatial processes. This method offers a computationally-simple approach, with easy-to-interpret findings. Overall, greenspaces in Portland do not appear to experience a concentration of crime. However, new patterns emerge as greenspace types and crime types are disaggregated. This study identified small parks within the city as experiencing a considerable concentration and specialization of crime, with this pattern remaining generally consistent when aggregate crime is broken down into discrete types. Some greenspace types are found to experience a concentration and specialization of certain crime subtypes, appearing to act as crime generators or attractors within their local environments. In contrast, other spaces exhibit potential protective factors against many crime categories, boasting lower-than-expected concentrations within their environs. This study demonstrates the importance of micro-level disaggregated local analysis to identify the unique local relationship between crime and urban features and to better inform prevention measures. It further emphasizes the value of methodological modifications, allowing for the incorporation of widely accessible spatial tools and widely available public data to explore connections between crime and meaningful public spaces. This is particularly important, as timely and specific information about these patterns can be of use to plan future spaces, shape existing spaces, and reduce local opportunities for crime and victimization. Given Portland's current emphasis on greenspace revitalization, the methods and findings within this study can provide support and targeted guidance for ongoing planning efforts and can ensure that the city's valued greenspaces remain a safe and engaging place for all users.

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About the Authors

Cheyenne Hodgen, M.S., is a PhD student at the University of California, Irvine. She received her Master of Science in Criminology and Criminal Justice from Portland State University. Her research interests focus on crime and place, specifically looking at the temporal and spatial patterns of different crime types at different locations.

Kathryn Wuschke, Ph.D., is an Associate Professor of Criminology and Criminal Justice at Portland State University. Her teaching and research interests focus on crime and place, specializing in Geographic Information Systems applications and methods. Her work centers on establishing and testing methods to measure and represent the connections between crime events and the built environment across spatial scales.

Appendix

Table 5: Portland Parks and Recreation Greenspace Type Coding

Classification Type	Code	Notes	Included in Study?
Park	1		Yes
Natural area	2		Yes
Arboretum Public garden Rose garden	3	Grouped as public garden	Yes
Community garden	4		Yes
Community and arts center Community school	5	Grouped as community and arts center or school	No
Memorial Museum	6	Grouped as memorial/museum	No
Swim pool (indoor) Swim pool (outdoor)	7	Grouped as swimming pool	No
Golf course	8		No
Raceway	9		No
Rental Facility	10		No