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Urban greenspace linked to lower crime risk across 301 major U.S. cities

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ABSTRACT

Greenspace enhances quality of life for urban residents in many ways, but it may also produce unexpected and undesired consequences. For example, a growing literature is exploring the relationship between greenspace and crime in cities, yielding mixed results. To address this question on a larger scale across diverse contexts, we used a multilevel modeling approach to investigate the relationship between different types of crime and urban greenspace in 59,703 census block groups within the 301 largest cities in the United States. After accounting for potential covariates of crime, including demographic, socioeconomic, and climate variables, we found that, on average, census block groups with more greenspace (measured by NDVI) had lower risk of both property ($\beta = -0.66$ [-0.70 to -0.61]) and violent crime ($\beta = -0.25$ [-0.28 to -0.22]). For property crime, this significant negative relationship held for all but one city in the sample (Cape Coral, FL), and no cities displayed a significant positive relationship. For violent crime a negative relationship was found for 289 cities and only three cities displayed a significant positive relationship (Chicago, IL, Detroit, MI, and Newark, NJ). Further research could strive to investigate the mechanisms fueling these significant and consistent trends and explore relationships between different types of crime and specific components and seasonal variations of greenspace.

1. Introduction

Urban greenspace (UGS), loosely defined as any type of plant-covered environment (public or private) located within a city (Taylor & Hochuli, 2017), is a key component of the city landscape, providing a variety of ecosystem services that improve quality of life in cities (Gómez-Baggethun & Barton, 2013; Tzoulas et al., 2007). Benefits of proximity to and use of UGS include increased physical activity (Kaczynski et al., 2008), improved mental health (Kaplan, 1995; Tsai et al., 2018), strengthened social cohesion (Peters et al., 2010), and enhanced subjective well-being (Larson et al., 2016). Collectively, these cultural ecosystem services have made UGS a hallmark of sustainable urban planning and design (Andersson et al., 2015; Chiesura, 2004). However, potential negative impacts of greenspace and vegetation are often overlooked (Crewe, 2001; Escobedo et al., 2011; Jennings et al., 2016; von Döhren & Haase, 2015). One potential consequence of UGS, exacerbated crime (Ceccato et al., 2020; Groff & McCord, 2012; Kim & Hipp, 2018), is of particular concern within many communities (Branas et al., 2013; Keith et al., 2018; Sreetheran & van den Bosch, 2014). In fact, fear of crime is often cited as a prominent barrier to greenspace development and subsequent use (Marquet et al., 2019; McCormack et al., 2010; Sreetheran & van den Bosch, 2014), and police forces often allocate resources to respond to the perceived potential for crime and disorder in specific types of greenspaces such as urban parks (Hilborn, 2009). But are these concerns warranted?

Reviews that synthesize existing studies reveal somewhat mixed results (see Bogar & Beyer, 2016; Mancus & Campbell, 2018; Shepley et al., 2019), and suggest that UGS may be both a generator and a deterrent of crime. UGS can limit visibility, leading to greater vulnerability to crime and reduction in the perceived safety of residents (Baran et al., 2018; Ceccato, 2014; Nasar et al., 1993). By reducing sightlines, UGS can also provide cover for criminals and illicit behavior in public spaces (Donovan & Prestemon, 2010; Mak & Jim, 2018; Michael et al., 2001). As posited by “broken windows” theory (Gau & Pratt, 2010), poorly maintained UGS, such as overgrown vegetation and litter, can communicate a lack of oversight and attract criminal activities

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(Nassauer, 1995; Sampson et al., 2017). Additionally, when UGS exists as public parks, it may be particularly conducive to crime generation (Demotto & Davies, 2006; Groff & McCord, 2012; Tower & Groff, 2014), especially if the park design does not follow key principles of crime prevention through environmental design (Ceccato et al., 2020; Jeffery, 1971; Newman, 1972).

On the other hand, many studies find that UGS is associated with reductions in crime. An often-cited case is Kuo and Sullivan's (2001b) study in Chicago, which found that greater vegetation density around public housing was associated with reduced crime among residents. Further research has supported these findings, extending the definition of what constitutes UGS from general vegetation to specific forms such as street trees (Donovan & Prestemon, 2010; Kondo, Han, et al., 2017), vacant lots (Branas et al., 2011, 2018), and tree canopy (Gilstad-Hayden et al., 2015; Schusler et al., 2018; Troy et al., 2012). In all of these studies, "greener" environments tend to correlate with decreases in crime. Mechanisms for explaining these relationships vary, but some scholars believe UGS improves the psychological health of urban residents by reducing typical precursors to crime such as stress and aggression (Markevych et al., 2017; Ulrich et al., 1991), improving attention (Kaplan, 1995), reducing cognitive fatigue (Kuo & Sullivan, 2001a; Tsai et al., 2018) and enhancing happiness and pro-social behavior (Frumkin et al., 2017; Kuo, 2015). UGS can also function as a crime deterrent by attracting diverse people, providing a space for positive social interactions via outdoor activity (Holtan et al., 2014; Maas et al., 2009) and promoting "eyes on the streets" or informal surveillance (Jacobs, 1961; Kuo & Sullivan, 2001b). This increased vigilance by community members can build collective efficacy, strengthening concern and watchfulness in a neighborhood (Ceccato et al., 2020; Cohen et al., 2008). For example, when revitalization projects transform vacant lots and deteriorating urban spaces into something more appealing and useful to residents, violence and crime typically decline (Branas et al., 2018). Crime reductions from municipal efforts to "clean and green" properties and areas of cities have been attributed to an increased sense of guardianship among residents (Heinze et al., 2018; Pizarro et al., 2020; Sadler et al., 2017). UGS also engenders greater levels of social connection and cohesion (Jennings & Bamkole, 2019; Peters et al., 2010) while bolstering social capital (Mullenbach et al., 2022), which can further strengthen local residents' commitment to protecting neighborhood space and deterring criminal activity.

Most studies have explored the relationship between UGS and crime within the context of single cities (Bogar & Beyer, 2016; Shepley et al., 2019), making extrapolation across larger scales difficult. One notable exception is Sanciangco et al. (2022), who found a negative link between greenspace and homicide rates across 290 major U.S. cities. Previous work is also constrained by other limitations, including the variables used to understand crime patterns. Several studies have focused only on violent crime (e.g., Sanciangco et al., 2022), based on the theory that vegetation reduces aggression by providing opportunities for mental restoration (Branas et al., 2018; Kuo & Sullivan, 2001a). Property crime, which is far more common, has been investigated to a lesser degree (Chen et al., 2016; Ye et al., 2018), and conclusions regarding the link between greenspace and crime often vary depending on the type of crime being studied (Bogar & Beyer, 2016). Few studies have considered multiple types of crime simultaneously.

Besides issues of scale, studies of the relationship between crime and greenspace face several other challenges. Crime is often linked to socioeconomic factors (Pratt & Cullen, 2005; Sampson & Groves, 1989), which may complicate interpretations. Many studies exploring UGS-crime connections therefore include some measure of income as a covariate of crime, while other variables such as education (Locke et al., 2017; Wolfe & Mennis, 2012) or residential characteristics such as home ownership (Gilstad-Hayden et al., 2015; Schusler et al., 2018) are used sporadically. Climatic variables such as temperature and precipitation also influence "greenness" of a city, but these features have rarely been considered in prior greenspace and crime research (Sanciangco et al., 2022; Tsai et al., 2018). This is a conspicuous omission considering the amount and distribution of green vegetation within a city is strongly influenced by climatic factors within a particular region (Kreft & Jetz, 2007; Stephenson, 1990). Furthermore, the term 'greenspace' is not clearly defined within the literature (Taylor & Hochuli, 2017). Across studies, the way in which greenspace has been operationalized varies, with some research measuring only street trees (Kondo, Han, et al., 2017) and others using satellite imagery (Sanciangco et al., 2022; Schusler et al., 2018) or a qualitative rating of vegetation (Kuo & Sullivan, 2001b).

Crime is therefore influenced by many factors (Zembroski, 2011), but environmental context – including UGS – is considered to be a key component (Kimpton et al., 2017). In the current study, we defined UGS to be all green vegetation within an area assessed through remotely sensed satellite imagery measured with the normalized difference vegetation index (NDVI) (Weier and Herring, 2000). This index and definition are commonly used in research exploring the associations between UGS and human behavior and health (Beyer et al., 2014; Gascon et al., 2016; Markevych et al., 2017; Wolfe & Mennis, 2012). The use of NDVI extends UGS beyond public spaces (e.g., parks) to include all aspects of green infrastructure within the built environment.

The variety of methods historically employed in prior research make it difficult to compare findings and gain a clearer picture of the crime and UGS relationship across diverse contexts (Bogar & Beyer, 2016). To overcome issues of scale and generalizability, our study incorporated a broad sample of cities – the 301 contiguous U.S. cities with a population over 100,000 – to extend understanding of the relationship between neighborhood-level crime risk (both violent and property crime risk) and UGS across a wide variety of cities.

Our approach is novel in several ways. First, our multi-level, multi-city analysis acknowledges that crime, and risk of crime, occurs in different amounts in different locations and is not uniform across a city (Brantingham et al., 2017; Weisburd, 2015). Using a multilevel model allowed us to treat cities as groups of census block groups, as opposed to treating the city as a homogeneous unit. This approach takes advantage of variation in neighborhood level data but also facilitates analysis across a large number of cities. Since our study was conducted, subsequent research has illustrated the value of looking across a large number of cities to assess correlates of crime and explore national trends (Sanciangco et al., 2022). Although our analysis spanned the entire country, it focused on the smallest unit of analysis available: census block groups. Many other studies exploring correlates of crime across multiple cities have focused on larger spatial scales, such as entire cities (Sanciangco et al., 2022; Stults & Hasbrouck, 2015). Treating cities as uniform units is a limitation that has been acknowledged in other work (Sanciangco et al., 2022). Second, our study simultaneously considered multiple types of crime, including both violent crime and property crime. Few previous studies have concurrently assessed both types of crime across multiple cities, with most opting to focus on violent crime (e.g., homicides; Sanciangco et al., 2022) even though property crime is more prevalent. Third, our study relied on a relatively novel data source (i.e., a crime risk index) to focus on crime risk rather than historical crime data (e.g., FBI UCR data). This was advantageous because it facilitated analysis at smaller spatial scales and standardized crime risk across diverse city neighborhoods, and provides an additional perspective to existing research on the greenspace and crime relationship.

2. Methods

To explore how UGS and crime risk are related, we collected data at the census block group (CBG) and city level for 301 cities with populations over 100,000 in the contiguous United States for 2015 (see Appendix for description and sources). Our unit of analysis was census block groups, the smallest geographical unit for which the U.S. Census Bureau collects detailed sociodemographic data. Due to the hierarchical nature of the data, with block groups nested within cities, we used a multilevel modeling approach to estimate the relationship between greenspace and crime across all cities in the study. This allowed for overall and city level estimates of how greenspace and crime are related.

Data were sourced from the U.S. Census Bureau to determine the sample cities based on population size, and cities with a population >100,000 in 2015 were included in the analysis. We retrieved values for sociodemographic variables 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). We retrieved spatial data from Census Bureau TIGER geodatabase for cities, using the census designation of 'places', which include incorporated municipalities. We selected block groups that were >50 % within city boundaries by calculating the intersection of block groups and municipal boundaries in R.

2.1. Dependent variable – crime risk index

Due to the broad scope of this study and variety of crimes considered, specific crime incident data (consisting of latitude, longitude, date, and time) was not consistently available across all cities. For this reason, we sourced crime risk data for census block groups in 2015 from Esri, Inc. who provide data on the relative crime risk for various geographic areas (Esri, 2016). This measurement is an index of crime risk that has been used in similar work on crime and greenspace (Grove et al., 2014; Locke et al., 2010; Troy & Grove, 2008). Other authors have compared the crime risk index to law enforcement incident data, finding the more general crime risk categories (e.g., violent, property) acceptable for large-scale analysis (Nau et al., 2019). This Esri dataset, while proprietary, provides estimated risk adjusted to align with federal crime data with the goal of creating a standardized data source that accounts for the numerous recording errors and idiosyncrasies inherent in the fragmented municipal law enforcement data across in the USA. Thus, the Esri data are analogous to similar data in epidemiology, where small area estimates of disease risk are generated from larger datasets (Zhang et al., 2015).

The crime risk 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 the Federal Bureau of Investigation (FBI) Uniform Crime Report (UCR) Part 1 crimes, covering violent and property crimes (Federal Bureau of Investigation, 2004). Our study used two crime risk types – all violent crime and all property crime – as the dependent variable. These two indices are found to best align with long-term incident level crime data (Nau et al., 2019). Violent crime is composed of assault, murder, robbery crimes. Property crime is composed of burglary, larceny, and auto theft.

2.2. Level 1 independent variables – block group characteristics

Greenspace - We operationalized greenspace 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 et al., 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, particularly in localized crime studies (Wolfe & Mennis, 2012). 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 et al., 2011). The value for NDVI was calculated based on Landsat 8 imagery for 2015 (from January through December), at 30-m resolution, using the Google Earth Engine platform (Gorelick et al., 2017). The maximum greenness across the year was calculated for each pixel, then used to calculate the mean for each census block group. A weighted mean was used for pixels partially in polygons. 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 and Herring, 2000). We transformed NDVI 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 census block group level. These variables represent the social conditions of an area that have been linked to crime in prior research on greenspace and crime (Land et al., 1990; Sampson et al., 2002; Sanciangco et al., 2022; Venter et al., 2022). The theoretical base for these variables stems from social disorganization theory, which links population characteristics with social conditions and crime (Jones & Pridemore, 2019; Kubrin & Weitzer, 2003; Shaw & McKay, 1972). To account for social conditions, we used data from the 2011–2015 5-year American Community Survey (ACS), which provides demographic sample-based estimates between the decennial census at the census block group level. The variables we used to assess socio-economic context were median household income, disadvantage index (Krivo & Peterson, 1996; Ulmer et al., 2012), diversity index (Sanciangco et al., 2022), percent of population under 18 (Sampson & Groves, 1989; Venter et al., 2022), and population density (Harries, 2006; Venter et al., 2022). The disadvantage and diversity indices, which integrate variables related to the social disadvantage of an area and its mix of racial groups, are described in more detail below.

Disadvantage Index - Because social disadvantage is associated with crime in the literature, we created an index from other demographic variables to approximate this construct (Bursik, 1988; Kubrin & Weitzer, 2003; Sampson & Groves, 1989). This index represents area social disadvantage within census block groups (Hughey et al., 2016; Krivo & Peterson, 1996; Sampson et al., 1997). Our measure was created from the mean z-score of the following variables following Krivo et al. (2009): percentage unemployed, percentage of families below poverty, percentage with less than high school education, and percentage of households that are female headed with no husband present and children under 18 years (female-headed families). The resulting score indicates if a block group is more or less disadvantaged than the average block group in the study, with positive values associated with greater disadvantage.

Diversity Index - We constructed a diversity index from the proportion 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. The index formula is: $\sum(p_i^2)$ where p_i is the proportion of each racial/ethnic group i in each census block group.

2.3. Level 2 independent variables – city context

City Crime Rate - We collected city level crime data 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). This aggregated crime rate is thought to reflect broader social conditions (or disorganization) in a city that might influence routine activities of residents and therefore opportunities for criminal activity or victimization (Cohen & Felson, 1979; Felson & Boba, 2010; Felson & Cohen, 1980; Jones & Pridemore, 2019). Consequently, city-level crime rates could predict local crime risk (Jones & Pridemore, 2019; McDowall & Loftin, 2009). This broad, aggregated measure of crime provided by local law enforcement agencies differs from the crime risk index in methodology, but it provides a contextual variable approximating the criminological condition of each city. Counts of the number of offenses and population were obtained for all cities (Federal

Bureau of Investigation, 2016). Using these counts, a rate per 1000 persons was calculated for violent and property crimes in 2015.

Police Force - Prior research has revealed associations between the size of a city's police force and crime (Lee et al., 2016; Levitt, 1997). For this reason, we used the size of the municipal law enforcement agency as a measure of the level of policing that exists within a city. We obtained the number of officers from FBI law enforcement employment data for 2015 and divided this by the city population (Federal Bureau of Investigation, 2016). Data related to deployment of officers across cities were not available. The police force variable is therefore the number of officers per 1000 persons citywide. Some cities were found to contract out law enforcement to county agencies. In such cases, we used the police force rate for the area served by a county law enforcement agency as a proxy for the city.

GDP - The gross domestic product (GDP), which provides a measure of "the value of the goods and services produced" within an area (U S Department of Commerce, 2015), is calculated for metropolitan regions across the United States. It measures the economic condition of a city, which is another contextual variable that is thought to contribute to crime (Andresen, 2015). This relationship is based on theories which postulate that the overall economic state of an area influences the level of guardianship and the opportunity to commit crime through employment, wages, and work hours (Andresen, 2015; Arvanites & Defina, 2006; Cohen & Felson, 1979). Additionally, cities with highly rated park systems typically spend more per resident on greenspaces, with GDP indicating variation in a city's ability to spend on greenspaces (The Trust for Public Land, 2019, 2020). To account for differences in the economic context of cities, we obtained the per capita metropolitan gross domestic product (GDP) from the Bureau of Economic Analysis.

Climate Type - A city's climatic region has a direct effect on the amount and type of vegetation that can grow there (Grace, 2008), and may also be linked to crime (Mares, 2013; Ranson, 2014; Sanciangco et al., 2022). It is key to define climate as the long-term trend and variability of weather conditions, different from weather at a specific time (IPCC, 2014a). Researchers have suggested that a measure of climate be included in future greenspace research to capture differences in land cover across regions (Tsai et al., 2018). One way that climate can be incorporated in analyses 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 et al., 2007). As our study focused only on the contiguous United States, the Köppen-Geiger classification did not provide adequate differentiation for the sample cities. As an alternative, we adopted a k-means clustering approach was taken that used mean 30-year temperature, mean 30-year precipitation, and mean number of days above 90 °F 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 were conceptualized as being a combination of average temperature, average precipitation, and number of days above 90 °F/32 °C - region 1: cool-dry-low (14.6 °C, 415 mm, 27 days), region 2: cool-wet-low (11.6 °C, 1049 mm, 16 days), region 3: warm-dry-high (19.2 °C, 351 mm, 108 days), and region 4: warm-wet-high (19.9 °C, 1233 mm, 81 days) (see Supplementary materials for map).

2.4. Analysis

We initially performed a bivariate analysis using Pearson's product moment correlations to test for significant associations between crime risk, greenspace, and the chosen covariates. To account for correlation within cities and to examine how the relationship varied across different cities, we used a multilevel modeling approach with census block groups nested within cities. The dependent variables in the modeling were the violent and property crime risk index value in each census block group. The independent variables at the block group level were mean NDVI (our measure of greenspace), median household income, disadvantage index, diversity index, percent of population under 18 years, and population density. The independent variables at the city level were crime rate per 1000 population, police officers per 1000 population, per capita GDP, and climate region.

Following the suggestion of Hox et al. (2010), we built statistical models 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-level variables, including climate region.

We fit linear multilevel models in R statistical software using the *lmer4* package (Bates et al., 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 the 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 et al., 2013; Singer & Willett, 2003).

We specified both random intercepts and random slopes 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 risk to vary across cities. We calculated standardized coefficients to facilitate comparison among variables in the model and their relative influence on crime risk.

2.4.1. Model descriptions

Model 1(null model): $crime\ risk_{ij} = \beta_0 + (1 \mid city)$

Model 2: model 1 $+ \beta_1\ NDVI_{ij} + \beta_2\ median\ income_{ij} + \beta_3\ disadvantage\ index_{ij} + \beta_4 diversity\ index_{ij} + \beta_5\ under\ 18_{ij} + \beta_6\ population\ density_{ij} + (NDVI_j \mid city)$

Model 3: model 2 $+ \beta_7$ per capita $GDP_j + \beta_8\ police\ force_j + \beta_9\ crime\ rate_j + \beta_{10}\ climate\ region_j$

As a sensitivity analysis we compared models with and without the city level crime variable of crime rate per 1000 persons. Models were compared using likelihood ratio tests to examine if including the city crime rate improved overall model fit and to confirm that the coefficient associated with mean NDVI did not practically differ across model iterations.

3. Results

Our sample included 62,086 census block groups (CBGs) across 301 major U.S. cities. Each of these census block groups was >50 % within city boundaries by area. Missing values were present due to data suppression by the US Census Bureau of household income in block groups with low populations (US Census Bureau, 2016), resulting in 59,703 complete cases (i.e., CBGs) used in the analysis. Descriptive statistics for level one and level two units are provided in Table 1. Correlations among the variables and potential collinearity in regression models were checked through bivariate analysis and variance inflation factor (VIF), and no issues were found (all correlations < 0.7 and VIF all < 2) (see Supplementary material for correlations).

The sensitivity analysis of city level crime rate compared the full model with and without crime rate per 1000 persons. Likelihood ratio test showed the full model with the crime rate variable had improved model fit for both violent crime risk (χ^2 (1) $= 167.0$, $p < 0.001$) and property crime risk (χ^2 (1) $= 113.7$, $p < 0.001$). The coefficient of interest, for mean NDVI, did not practically differ between the two model specifications (0.3 for violent crime risk and 0.1 for property crime risk). For these reasons the full model, with city crime rate, was used for the analysis.

Table 1
Descriptive statistics for census block groups and cities included in the analysis (n = 59,703 - block groups; n = 301- cities).

Variable	Mean	SD	Min	Max	Median
Census block groups - level 1					
Crime risk index - violent	179.79	161.51	2	1334	131
Crime risk index - property	135.95	92.35	3	1030	118
Disadvantage index	0.05	0.79	−1.19	4.28	−0.12
Diversity Index (×100)	47.64	21.43	0	87.93	51.99
Median household income (000)	55.67	32.88	2.5	250	48.15
Mean NDVI value (×10)	4.07	1.52	0.51	8.06	4.15
Percent under 18 years old	22.29	9.7	0	69.66	22.33
Area (sq. km.)	1.05	3.47	0.004	222.97	0.47
Total population	1444	846.09	23	22,054	1265
Population density (per sq. km.)	5609.94	9882.09	4.18	220,954.5	2557.27
Cities - level 2					
Per capita GDP (000)	56.61	14.91	20.46	178.31	57.75
Police officers per 1000	2.52	1.39	0.09	5.86	2.07
City property crime rate (per 1000)	34.45	13.92	9.95	93.31	34.4
City violent crime rate (per 1000)	6.91	3.75	0.51	18.17	5.97
Number of census block groups per city	198.35	409.11	28	5869	100

The initial null model, Model 1, provided the variance for calculation of the intraclass correlation (ICC) value for violent crime risk (0.344), property crime risk (0.322), and NDVI (0.695). The ICC indicated that there was variation in the block group crime risk and NDVI at the city level, providing support for using a multilevel modeling approach. In the study sample, 34.4 % of the variation in the violent crime risk index and 32.2 % of the variation in the property crime risk index was due to differences between cities.

Model 2, as an intermediate model, introduced the level 1 CBG variables of mean NDVI, median household income, racial/ethnic diversity, social disadvantage, percent of population under 18 years old, population density (Tables 2 and 3). NDVI was also added as a random slope to allow the estimate of the UGS relationship to crime risk to vary across cities. Model 2 was an improved fit over the baseline model based on Akaike Information Criterion (AIC) and likelihood ratio tests (LRT) for both the violent crime risk model (ΔAIC: 31427.15; LRT: χ^2 (8) = 31,459, $p < 0.001$) and the property crime risk model (ΔAIC: 21104.2; LRT: χ^2 (8) = 21,141, $p < 0.001$).

The final model, Model 3, included the addition of level 2 (city level) variables of per capita GDP, per capita police force, the city's rate of crime per 1000 population, and climate region (Tables 2 and 3). AIC and LRT showed that model 3 was an improved fit over Model 2, which included only block group level variables, for both violent crime risk (ΔAIC: 299.8; LRT: χ^2 (6) = 292.41, $p < 0.001$) and property crime risk (ΔAIC: 338.4; LRT: χ^2 (6) = 335.49, $p < 0.001$). The psuedo-R^2 suggested the full models yielded moderate predictive power with respect to violent crime risk (pseudo-R^2 = 0.7867) and property crime risk (pseudo-R^2 = 0.7315). All variables except Per Capita Police were statistically significant in the violent crime risk model (Table 2). In the property crime risk model, Per Capita Police was also the only variable not significant (Table 3). The slope coefficient for NDVI (i.e., greenspace) in the violent crime model indicated a negative relationship, with a 0.1 increase in NDVI associated with a decrease of 26.7 % in violent crime risk when all other variables are at their average. For property

Table 2
Results of multilevel model examining relationship between urban greenspace (NDVI) and violent crime risk in the 301 largest U.S. cities.

Predictors	Model 1				Model 2				Full model			
	Beta	*CI*	*std. Beta*	*Standardized CI*	*Beta*	*CI*	*std. Beta*	*Standardized CI*	*Beta*	*CI*	*std. Beta*	*Standardized CI*
Intercept	**144.48**	**134.30–154.66**	**−0.22**	**−0.28 to −0.16**	**170.15**	**159.44–180.86**	−0.06	−0.13–0.01	**174.76**	**161.13–188.40**	−0.03	−0.12–0.05
NDVI mean					**−24.39**	**−28.04 to −20.75**	**−0.23**	**−0.26 to −0.19**	**−26.68**	**−30.09 to −23.27**	**−0.25**	**−0.28 to −0.22**
Median household income					**−0.65**	**−0.68 to −0.61**	**−0.13**	**−0.14 to −0.12**	**−0.64**	**−0.67 to −0.60**	**−0.13**	**−0.14 to −0.12**
Disadvantage index					**89.23**	**87.55–90.92**	**0.44**	**0.43–0.45**	**88.88**	**87.20–90.57**	**0.44**	**0.43–0.44**
Diversity index					**−0.80**	**−0.85 to −0.76**	**−0.11**	**−0.11 to −0.10**	**−0.8**	**−0.84 to −0.75**	**−0.11**	**−0.11 to −0.10**
Percent under 18					**−0.60**	**−0.70 to −0.49**	**−0.04**	**−0.04 to −0.03**	**−0.59**	**−0.69 to −0.48**	**−0.04**	**−0.04 to −0.03**
Population density (per sq. km)					**−1.61**	**−1.73 to −1.49**	**−0.10**	**−0.11 to −0.09**	**−1.61**	**−1.73 to −1.49**	**−0.10**	**−0.11 to −0.09**
Per capita GDP (000)									**0.46**	**0.12–0.79**	**0.04**	**0.01–0.07**
Per capita police (000)									1.05	−6.11–8.21	0.01	−0.05–0.07
City crime rate-violent									**15.26**	**13.63–16.89**	**0.35**	**0.32–0.39**
Climate region [cool-wet-low][a]									**36.79**	**22.18–51.40**	**0.23**	**0.14–0.32**
Climate region [warm-dry-high][a]									−17.47	−36.92–1.98	−0.11	−0.23–0.01
Climate region [warm-wet-high][a]									**32.46**	**16.77–48.15**	**0.2**	**0.10–0.30**
Random effects												
σ^2	17,121.64				10,012.26				10,022.22			
τ_{00}	7946.91				8647.91				2510.25			
τ_{11}					838.05				695.6			
Pseudo R^2	–				0.7870				0.7867			
AIC	752,646.6				721,219.5				720,919.6			

Estimates in **Bold** – $p < 0.05$.
[a] Reference climate region: cool-dry-low.

Table 3
Results of multilevel model examining relationship between urban greenspace (NDVI) and property crime risk in the 301 largest U.S. cities.

Predictors	Model 1				Model 2				Full model			
	Beta	*CI*	*std. Beta*	*Standardized CI*	*Beta*	*CI*	*std. Beta*	*Standardized CI*	*Beta*	*CI*	*std. Beta*	*Standardized CI*
Intercept	**133.89**	**128.03–139.75**	−0.02	−0.09–0.04	**156.3**	**146.76–165.84**	**0.22**	**0.12–0.32**	**104.5**	**92.34–116.66**	**−0.34**	**−0.47 to −0.21**
NDVI mean					**−38.59**	**−41.47 to −35.71**	**−0.63**	**−0.68 to −0.59**	**−39.93**	**−42.71 to −37.14**	**−0.66**	**−0.70 to −0.61**
Median household income					**−0.18**	**−0.20 to −0.15**	**−0.06**	**−0.07 to −0.06**	**−0.17**	**−0.20 to −0.15**	**−0.06**	**−0.07 to −0.05**
Disadvantage index					**22.06**	**20.99–23.13**	**0.19**	**0.18–0.20**	**22.03**	**20.96–23.09**	**0.19**	**0.18–0.20**
Diversity index					**0.05**	**0.02–0.08**	**0.01**	**0.00–0.02**	**0.05**	**0.02–0.08**	**0.01**	**0.01–0.02**
Percent under 18					**−1.47**	**−1.53 to −1.40**	**−0.15**	**−0.16 to −0.15**	**−1.46**	**−1.53 to −1.40**	**−0.15**	**−0.16 to −0.15**
Population density (per sq. km)					**−0.99**	**−1.07 to −0.91**	**−0.11**	**−0.11 to −0.10**	**−0.99**	**−1.07 to −0.92**	**−0.11**	**−0.11 to −0.10**
Per capita GDP (000)									**−0.51**	**−0.80 to −0.22**	**−0.08**	**−0.13 to −0.04**
Per capita police (000)									−1.45	−7.20–4.30	−0.02	−0.11–0.06
City crime rate-property									**2.65**	**2.31–2.99**	**0.40**	**0.35–0.45**
Climate region [cool-wet-low][a]									**82.12**	**69.34–94.91**	**0.89**	**0.75–1.03**
Climate region [warm-dry-high][a]									−5.99	−22.46–10.49	−0.06	−0.24–0.11
Climate region [warm-wet-high][a]									**78.59**	**64.95–92.22**	**0.85**	**0.70–1.00**
Random effects												
σ^2	5784.32				3998.09				3998.72			
τ_{00}	2634.83				6972.94				2110.41			
τ_{11}					557.97				508.32			
Pseudo R^2	–				0.7316				0.7315			
AIC	687,852.9				666,748.7				666,410.3			

Estimates in **Bold** – $p < 0.05$.

[a] Reference climate region: cool-dry-low.

crime risk, a 0.1 increase in the NDVI coefficient was associated with a 39.9 % decrease in crime risk.

The random slope of NDVI allowed for an estimate of the UGS and crime relationship across cities. For property crime risk the estimated means for the cities in the study ranged from −192 to +0.6, with all but one city (Cape Coral, FL) indicating a negative relationship and zero indicating a significant and positive relationship. For violent crime risk the estimates ranged from −154 to +22, with 289 of the 301 cities indicating a negative relationship and just three indicating a significant and positive relationship. UGS was associated with increased violent crime risk in block groups for just three cities: Chicago, IL, Detroit, MI, and Newark, NJ. Each of these cities had positive coefficients for the NDVI slope estimate considering a 95 % confidence interval.

Figs. 1 and 2 present the standardized coefficients from the final models. In addition to NDVI, other variables with a strong effect on crime risk in the final model were the disadvantage index and city crime rate (Figs. 1 and 2). CBGs with more social disadvantage showed an increase in both types of crime risk, as did CBGs in cities with higher levels of crime reported at the city level. The ethnic/racial diversity index flipped signs between violent and property crime risk models, indicating that greater ethnic and racial diversity was associated with less violent crime risk and slightly greater property crime risk. The percentage of the population under 18 was a weak predictor for violent crime risk but had a stronger association with property crime risk. Relative to regions with cool-dry-low climates, regions with cool-wet-low and warm-wet-high climates were associated with greater violent and property crime risk.

4. Discussion

Our results showed that, on average across the 301 largest cities in the contiguous United States, and even after accounting for a variety of potential crime correlates, more UGS in a neighborhood (i.e., census block group) was consistently and significantly associated with reduced risk of both violent and property crime. Results of both multilevel models indicated good fit with moderate predictive power. Of all variables in our models, the strongest negative predictor of both violent crime ($\beta = -0.025$) and property crime ($\beta = -0.66$) was NDVI, our measure of UGS (see Figs. 1 and 2).

Our study aligns with prior work showing areas with greater greenspace are found to have lower crime (Shepley et al., 2019), but on a larger scale and with a greater variety of crime considered relative to previous studies (Sanciangco et al., 2022; Venter et al., 2022). We investigated the relationship between crime risk and UGS across 59,703 census block groups in multiple U.S. cities and found similar results to research done in only single cities. For instance, similar patterns showing inverse associations between vegetation and crime rates have been documented in Philadelphia, PA (Branas et al., 2018; Kondo, South, et al., 2017; Wolfe & Mennis, 2012), Chicago, IL (Kuo & Sullivan, 2001b; Schusler et al., 2018), New Haven, CT (Gilstad-Hayden et al., 2015), and Baltimore, MD (Troy et al., 2012). Many of these previous studies used differing methods. Our results provide new evidence that this relationship is not unique to specific methodological approaches or urban contexts.

Though on average more UGS was associated with less crime, our modeling approach also showed variation in crime risk and the relative influence of NDVI across cities. Remarkably, all but one of the 301 cities in the study revealed a negative relationship between property crime risk and UGS, which supports previous work on property crime and UGS (Ye et al., 2018). Yet, the estimated effect of UGS on property crime risk varied across cities from −192 to +0.6 (see Supplementary material fig. S2), indicating that the impact of UGS on property crime was not identical across cities in the study and could vary from minimal to extreme. We would expect the impact of UGS to lie within this wide range, with the highest density between −75.1 and −1.7 (95 %), pointing to decreases in property crime risk of 2 % to 75 % as block

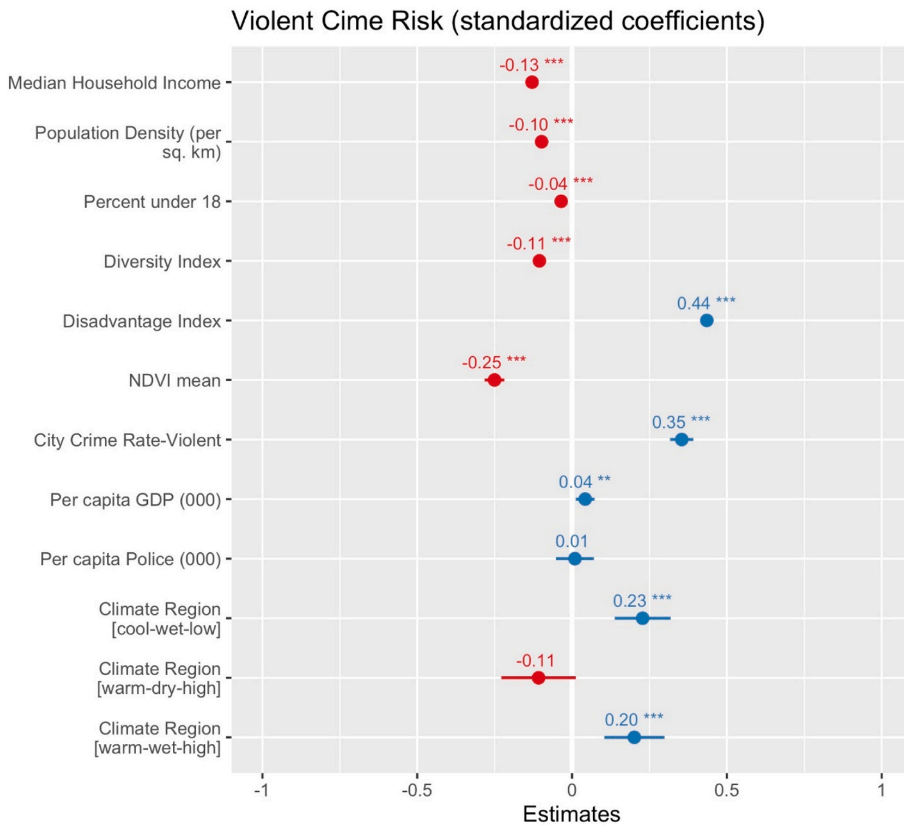

Fig. 1. Forest plot of estimated standardized model coefficients and confidence intervals from full model. Dependent variable - violent crime risk.

Fig. 2. Forest plot of estimated standardized model coefficients and confidence intervals from full model. Dependent variable - property crime risk.

groups increase in greenspace (a change in NDVI of +0.1). Such increases could come from the planting of trees or conversion of paved spaces to green vegetation.

Heterogeneity also existed when assessing the association of NDVI with violent crime risk, as coefficients across cities ranged from −154 to +22 (see Supplementary material Fig. S3), with the highest density between −81.2 and +12.5 (95 %). For violent crime, three cities showed significant positive association between UGS and crime risk – Chicago, IL, Detroit, MI, and Newark, NJ. In these three cities, greater UGS was related to increased violent crime risk within neighborhoods. As other studies have indicated, this suggests that UGS may not have an exclusively negative relationship with violent crime risk (Bogar & Beyer, 2016; Shepley et al., 2019). These three cities did not consistently exhibit characteristics in our data that particularly stood out. Detroit had the highest mean violent crime risk and lowest median income of all the cities, but Chicago and Newark did not rank as extreme on the median income spectrum. Detroit and Newark were in the top three cities for social disadvantage, but Chicago was much lower in rank on this metric. The unique criminogenic context of these particular cities may be driven by other social, economic, and cultural variables that were not accounted for in our models, such as neighborhood disinvestment and abandonment (Raleigh & Galster, 2015). Declining areas of these cities could also suffer from greater amounts of vacant land, communicating a lack of care and offering settings for criminal activity (Branas et al., 2018; Newman et al., 2016). These cities' high degree of racial segregation might also lead to concentrations of violent crime (Krivo et al., 2009; Social Science Data Analysis Network & Frey, 2011). While we did measure racial and ethnic diversity at the census block group level, extreme segregation across a city could be a factor to consider in future greenspace and crime research.

Our work does not support the idea that vegetation in general is a cause of crime, though aspects such as concealment or impaired visibility in specific urban locations might present unique challenges (Felson & Boba, 2010; Fischer & Nasar, 1992; Michael et al., 2001). It should be noted, however, that this study did not address perceptions or fear of crime that may arise from vegetation in neighborhoods (Baran et al., 2018; Sonti et al., 2020; Sreetheran & van den Bosch, 2014). More research using primary data collection with individual residents can help to explore these possibilities, highlighting the unique personal experiences that shape the relationship (real and perceived) between greenspace and crime in cities.

Additionally, yet not surprisingly, most crime covariates in our models (other than NDVI) were also significant in the anticipated direction. Confirmation of these hypothesized relationships helped to validate our models. For example, the strongest positive predictor of violent crime risk within block groups was social disadvantage (see Fig. 1), which other studies have also corroborated (Krivo & Peterson, 1996; Ulmer et al., 2012). However, considering the standardized coefficients for all variables, NDVI had the strongest negative effect on both property crime risk ($\beta = -0.66$) and violent crime risk ($\beta = -0.25$) relative to other variables in the model (see Figs. 1 and 2). The contextual variables of city crime rate and climate region showed a greater influence on property crime risk than was seen with violent crime risk. Although social and physical conditions interact to influence crime risk in different ways across diverse urban environments (Ceccato et al., 2020; Shepley et al., 2019), our results suggest that the crime-reducing potential of greenspace is relatively consistent and may transcend city context.

4.1. Limitations and future research

Future research on greenspace and crime could address several limitations of this study. First, we used a crime risk index derived from modeling of various data sources (Esri, 2016), rather than crime data reported through the FBI's Uniform Crime Reporting (UCR) program (e.g., Sanciangco et al., 2022), to estimate the amount of crime risk in each neighborhood (i.e., CBG) unit. Estimation of the crime risk index was advantageous to this research because it provided a standardized relative measure of risk and broad geographic coverage for small areas where FBI or local data is not available. However, all crime data contain errors that are inherent in crime reporting (Langton et al., 2012; Maltz, 1999; Pepper et al., 2010; Piquero et al., 2014), and the crime risk index may therefore be affected by any error in the underlying crime statistics. Despite this limitation, the crime risk index is the only broadly available data source reliably spanning multiple types of crime, and it has shown some promise in estimating risk of property and violent crime (Nau et al., 2019), including their relationship to greenspace (Grove et al., 2014; Locke et al., 2010; Troy & Grove, 2008). Additionally, because we focused on large cities in our study, we cannot evaluate how these findings might manifest in smaller municipalities where crime data is even more scarce and fragmented.

Second, this study offers a cross-sectional view of the relationship between UGS and crime. Temporal trends, such as decreasing or increasing crime, and historical shifts in municipal investment in and public perceptions of greenspace were not considered. However, these temporal trends have been shown to influence real and perceived connections between greenspace and crime, both in positive (Gobster, 1998; Sanciangco et al., 2022) and negative ways (Stodolska et al., 2009). Use of a cross-sectional approach also limits inference about causal effects of UGS and greenspace development on crime. Furthermore, we modeled the UGS and crime risk relationship with linear multilevel methods for interpretability and to link to previous research. Future work could investigate non-linear relationships between crime risk, UGS, and other covariates.

Third, our study only considered a broad definition of UGS, operationalized by NDVI, to align with the majority of prior research on greenspace and crime. However, humans typically experience greenness differently than an overhead (i.e., satellite) view. More detailed measures of vegetation, such as street-level imagery and land cover datasets, are becoming increasingly available and could be included in future studies of the relationship to investigate how the type and structure of UGS may relate to crime (King & Locke, 2013; Larkin & Hystad, 2018; Santos et al., 2016; Seiferling et al., 2017). Also important to consider is the specific influence of public parks on crime. Parks represent one type of managed urban greenspace that is particularly common in large cities. When UGS exists as public parks, it may inadvertently contribute to crime generation by creating spaces where potential victims congregate and public surveillance falters (Demotto & Davies, 2006; Groff & McCord, 2012; Tower & Groff, 2014). This crime generation potential of parks may be mitigated through the principles of crime prevention through environmental design (Ceccato et al., 2020).

Overall, the potentially differential impacts of different types of greenspace on different types of crime underscore the need for more research exploring the mechanisms behind the UGS-crime relationship (Shepley et al., 2019; Venter et al., 2022). For instance, the stronger inverse relationship between greenspace and property crime (1 s.d increase in NDVI to 0.66 s.d decrease in crime risk) warrants additional inquiry, as property crime is much more common but has received less attention compared to violent crime in the literature (Ye et al., 2018). Variable patterns of crime risk across different climate regions also suggest some degree of heterogeneity worthy of investigation. Some initial consideration of climate has been done by Sanciangco et al. (2022), but further research is needed on the role climate may play in the crime and greenspace dynamic beyond mean temperatures, considering especially the increased number of extreme heat events predicted in the future (Hsiang et al., 2013; IPCC, 2014b; Ranson, 2014).

Situations that provide opportunities for natural experiments, such as interventions that create new or alter existing UGS, could also be investigated to observe what impacts arise from these interventions and why (Garvin et al., 2013; Kondo, Han, et al., 2017; Pizarro et al., 2020; South et al., 2018). Such an approach, coupled with data collection strategies that illuminate residents' lived experiences, could help to reveal the elusive causal mechanisms driving the inverse relationship between greenspace and crime risk observed in this study.

5. Conclusion and implications

Urban greenspace provides a variety of ecosystem services that can enhance the well-being of city residents (Larson et al., 2016; McPhearson et al., 2014; Remme et al., 2021), but the effects of UGS on crime has been the subject of substantial debate (Bogar & Beyer, 2016; Ceccato et al., 2020; Jennings et al., 2016). Our study demonstrated that, on average across 301 U.S. cities, increased UGS at the neighborhood level is associated with decreased violent and property crime risk across almost every urban context. Unlike many previous studies focusing on single cities, our multi-level, multi-city analysis adds to other work on this topic (e.g., Sanciangco et al., 2022) and enabled us to account for heterogeneity in social and criminological context across urban areas that might influence the relationship between greenspace and crime. Our analysis extends existing research on the greenspace-crime relationship by accounting for different types of crime risk, incorporating a novel data source on relative crime risk that can be estimated at fine spatial scales, modeling the relationship by using data at the neighborhood level, and applying the same analysis across multiple city contexts. Our approach allowed us to quantify sources of heterogeneity and similarities in the relationship between UGS and crime risk that might transcend municipal boundaries.

Strategic integration of UGS into urban crime prevention strategies offers many potential advantages. Policies and interventions focused on UGS provide a positive and less controversial approach to crime prevention than more aggressive enforcement models, embracing some of the key principles of crime prevention through environmental design (CPTED) (Cozens, 2002). As an added bonus, the creation or improvement of UGS fuels other positive outcomes such as physical activity (Cohen et al., 2019) and neighborhood cohesion (Peters et al., 2010). For all of these reasons, crime prevention strategies that utilize UGS and other environmental factors may be preferable to reactive policing measures that attempt to curtail crime through actions such as increased arrests for low-level offenses (Sullivan & O'Keeffe, 2017). Proactive UGS-based approaches to crime prevention may be even more important following the COVID-19 pandemic, which has produced unprecedented challenges to mental health and social instability on a global scale (Wu et al., 2021).

Our expansive national analysis reveals how urban greening could help to create safer neighborhoods with less crime, possibly by providing spaces for recreation, restoration, and positive social interactions (Fan et al., 2011; Lee et al., 2015). However, planners and managers must also consider the consequences of greenspace-mediated crime prevention, which can fuel changes in community social structure and gentrification that generate unexpected negative outcomes, potentially displacing crime to less green neighborhoods (Harris et al., 2018, 2019; Rigolon & Németh, 2019). In many cases, the variety of health and well-being benefits that UGS provides might outweigh these potential costs, especially if greenspace projects are carried out in concert with residents to create green and just cities (Cole et al., 2019; Rigolon et al., 2019). Overall, evidence from this and related studies can be used to promote the value of UGS in urban planning and development both in the United States and internationally (Jennings et al., 2017; Larson et al., 2016; Sushinsky et al., 2017; Venter et al., 2022), particularly as a tool for reducing crime and improving both the social and natural environment of cities.

CRediT authorship contribution statement

S. Scott Ogletree: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Lincoln R. Larson:** Writing – review & editing. **Robert B. Powell:** Writing – review & editing. **David L. White:** Writing – review & editing. **Matthew T.J. Brownlee:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

A link to data and code has been included in the attached file manuscript. Data, code, and supplementary description available at https://osf.io/vumy9/.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2022.103949.

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