The relationship between city 'greenness' and homicide in the US: Evidence over a 30-year period

Jonnell C. Sanciangco[1], Gregory D. Breetzke[2], Zihan Lin[1], Yuhao Wang[1], Kimberly A. Clevenger[1], Amber L. Pearson[1,3,*]

[1]Michigan State University, East Lansing, MI, USA
[2]University of Pretoria, Pretoria, South Africa
[3]University of Otago, Wellington, New Zealand

*Correspondence to *Amber L. Pearson. Email:* apearson@msu.edu

Abstract

Residents in US cities are exposed to high levels of stress and violent crime. At the same time, a number of cities have put forward 'greening' efforts which may promote nature's calming effects and reduce stressful stimuli. Previous research showed that greening may lower aggressive behaviors and violent crime. In this study we examined, for the first time, the longitudinal effects over a 30-year period of average city greenness on homicide rates across 290 major cities in the US, using multilevel linear growth curve modeling. Overall, homicide rates in US cities decreased over this time-period (52.1 to 33.5 per 100,000 population) while the average greenness increased slightly (0.41 to 0.43 NDVI). Change in average city greenness was negatively associated with homicide, controlling for a range of variables ($\beta = -0.30$, p-value=0.02). The results of this study suggest that efforts to increase urban greenness may have small but significant violence-reduction benefits.

Keywords: Crime; urban greening; greenspace; NDVI; growth curve model

Introduction

Urban dwellers in the United States (now 81% of the total population (United States Census Bureau, 2016)) are exposed to a large number of negative externalities including excessive noise (World Health Organization, 2011), low air quality (Setälä, Viippola, Rantalainen, Pennanen, & Yli-Pelkonen, 2013), light pollution (Longcore & Rich, 2004), traffic congestion (Boyko & Cooper, 2014) and violent crime (Office for Victims of Crime, 2017), among others. Urban environments have also been found to adversely impact an individuals' ability to process stressful situations. Indeed, this was shown by Lederbogen and colleagues (2011) who used functional magnetic resonance imaging to link the urban environment to specific neural processes. The researchers showed how urban living adversely affected the functioning of a key part of the brain (the perigenual anterior cingulate cortex) that regulates negative affect and stress. The result is an increase in risk for various types of psychological disorders including depression, anxiety, and mental fatigue (Kuo & Sullivan, 2001a; Peen, Schoevers, Beekman, & Dekker, 2010; Wandersman & Nation, 1998; World Health Organization, 2011). In contrast, natural or 'green' environments have been found to provide both visual and auditory cues that reduce overall stress (Roe et al., 2013; Tyrväinen et al., 2014), anxiety (Roe, Aspinall, Mavros, & Coyne, 2013), anger (Bowler, Buyung-Ali, Knight, & Pullin, 2010), and rumination (Bratman, Daily, Levy, & Gross, 2015; Bratman, Hamilton, Hahn, Daily, & Gross, 2015).

The psychological benefits of being in contact with and/or exposed to nature may also lower an individual's propensity for aggression and violence. The causal pathway through which this may occur is multifactorial and complex with a number of theories being espoused to explain this association. One prominent theory that has been commonly used to explain the aggression-nature linkage is attention restoration theory (ART). ART posits that natural features attract our involuntary attention, allowing for the restoration of directed attention, which is required for cognitive control (Berman, Jonides, & Kaplan, 2008; Berto, 2005). The theoretical linkage between greenness and violence is, therefore, indirect and mediated by self-control restoration. The ability to assert cognitive control (i.e., self-control) is critical to not only block out extraneous stimuli, but also to inhibit or suppress undesirable thoughts, feelings, or behaviors (Kaplan & Kaplan, 1989; Kuo & Sullivan, 2001a). Accordingly, the presence of nature can lead to the inhibition of violent or aggressive behavior (Kaplan & Kaplan, 1989; Kuo & Sullivan, 2001a; Staats, Jahncke, Herzog, & Hartig, 2016; Wilkowski & Robinson, 2008; Wilkowski, Robinson, & Troop-Gordon, 2010) and potentially lower rates of certain types of interpersonal crimes such as homicide. Another reason for the potential for 'greenness' to lower neighborhood crime relates to the ways in which nature impacts human behavior. According to Jacobs' (1961) influential 'eyes on the street' theory, greenspaces encourage surveillance by people using these spaces legitimately thereby reducing the opportunities for criminal behavior. Jacobs' theory is based on the premise that the public will attempt to stop and/or prevent criminal behavior if they witness it and in doing so provide community guardianship to collectively work to prevent or reduce crime. For instance, legitimate users of greenspaces (parks, community gardens, greened thoroughfares, sporting fields and ovals) may reprimand people engaging in illegal activity and/or contact law enforcement if they witness a crime. More recent research has, however, shown that greenspace amenities may either limit or generate crime depending on the public behavior they promote (Kimpton, Corcoran, & Wickes, 2017). Greenspaces with new and/or improved amenities may reduce certain types of crime (Brantingham & Brantingham, 1993; Knutsson, 1997) while greenspaces with crumbling and/or dilapidated amenities may increase the risk of crime (Groff & McCord, 2012; Rhodes et al., 2007).

Previous research has most often however found negative associations between the presence of nature and various types of crime (Donovan & Prestemon, 2012; Kondo, Hohl, Han, & Branas, 2016; Kondo, South, Branas, Richmond, & Wiebe, 2017; Kuo & Sullivan, 2001b; Snelgrove, Michael, Waliczek, & Zajicek, 2004; Troy, Grove, & O'Neil-Dunne, 2012; Mary, Wolfe & Mennis, 2012). That is, higher percentages of nature and/or levels of 'greenness' at various scales (ranging from neighborhood to city) have been found to be associated with lower rates of crime across a range of categories. 'Greenness' in this instance refers to various types of visible green vegetation (James, Banay, Hart, & Laden, 2015) such as shrubs and trees present in the urban environment (also referred to as 'greenspace' or natural environments). A limited number of studies have also examined the effect of 'greening' or greenness on crime levels over time (Branas et al., 2011; Burley, 2018; Harris, Larson, & Ogletree, 2018; Sadler, Pizarro, Turchan, Gasteyer, & McGarrell, 2017). The vast majority of these studies have also found a decrease in crime over time (ranging from a few years to a decade) after various greening effects. For example, Burley (2018) found a reduction in violent crime after a tree planting intervention (e.g., for every 100 trees planted, there were 24 fewer violent crimes the following year) over a five-year period in Portland, Oregon while Harris et al. (2018) found that the presence of a recreational trail lowered crime rates over five-year period in Chicago, Illinois. Other researchers have found a decrease in crime over a decade after the greening of vacant lots (Branas et al., 2011; Branas et al., 2018; Garvin, Cannuscio, & Branas, 2013; Sadler et al., 2017). Whilst these examples provide some evidence of the potential for added greenness to contribute to reductions in crime over time, these studies are most often context-specific reducing their generalizability to other cities.

Thus despite a plethora of research in this area, there are still a number of gaps; notably the dearth of studies examining this association across multiple cities and over a substantial period of time. It could be that the results of prior studies are context-specific and/or are pertinent to one particular point in time. In this study we aim to examine how homicide trends vary in relation to levels of city greenness, and to ascertain whether this variation is context-specific or relatable at a national level. In fact, to our knowledge, this is the first empirical study examining the effects of greenness on homicide in multiple cities across the US over time; and certainly the first of its kind at a national scale.

The current study

The main aim of this study is to investigate the relationship between urban greenness and homicide over a 30-year period (1986–2015) across all major US cities. In achieving this aim, the study will make a number of important contributions to the extant literature. First, we will examine the relative importance of 'greenness' and its impact on homicide over an extended period of time. Most previous longitudinal research examining the impact of greenness on crime examine this association over a few years or up to a decade; in this study we explore the relative importance of urban greenness on crime over 30 years. Second, an important nationwide perspective is provided in contrast to existing context-specific studies undertaken most often across numerous cities in the United States. This is important in terms of establishing a frame of reference for future studies of this nature conducted outside the US. Ratcliffe (2010) notes that the most under-researched area of spatial criminology lies in spatial and temporal crime patterning, and prediction. Third, the study aims to provide a better understanding of the unique yet interdependent role that other factors play in understanding the crime-greenness linkage. We therefore aim to answer the following research questions: does greenness reduce the risk of homicide across varying contexts over time? And do other factors also play a facilitating role?

There are a number of reasons why this study is important but perhaps the most pertinent one relates to a changing climate and its effect on nature and subsequent human behavior. Indeed, climate change over the next century is predicted to radically alter the ways cities and their environs appear, and how humans subsequently act (Hu, Wu, Chen, Sun, & Li, 2017; Landauer, Juhola, & Klein, 2018). Understanding the climate-cities-behavior nexus is therefore crucial for future mitigation and planning actions in both a developed and developing context. With specific reference to this study, it is increasingly clear that a changing climate will alter water cycling with subsequent effects on vegetation and plant growth. Indeed, there is growing evidence that climate change has already greatly impacted land degradation (Webb et al., 2017), desertification (Eskandari, Borji, Khosravi, & Mesbahzadeh, 2016) and land use change (Edmonds & Rosenberg, 2005) globally. Recent evidence has shown how climate change also impacts levels of greenness in cities (Jiang et al., 2017; Kong, Zhang, Singh, & Shi, 2017; Tong et al., 2019). This interdependence between climate, levels of greenness and criminal behavior is further explored in this study.

Data and methods

Homicide data

City-level crime data were obtained from the Federal Bureau of Investigation (FBI)'s Uniform Crime Reporting (UCR) online reporting tool. Homicide cases for 290 American cities across 45 states for each year from 1986 to 2015 were extracted from the crime dataset and used as the outcome variable of interest in this study (see Table S1). According to the FBI (2018) there are three variables that make up the overall variable of homicide: murder and non-negligent manslaughter; negligent manslaughter; and justifiable homicide. Due to the changes in how negligent manslaughter and justifiable homicide have been defined over the 30-year time period of this study, they were excluded from the study and only murder and non-negligent manslaughter were included in the analyses. These two latter crime types were then extracted across the 30-year study period for each of the 290 cities. Only cities with a population of 100,000 were included here, as this is the inclusion criteria for FBI crime reporting. Homicide was used as a crime type to analyze in this study for two reasons; first, homicide greatly impacts residents' sense of personal safety and security (Skogan, 1990), and second, this type of crime provides the most objective assessment of violent crime risk in cities as a result of it being most difficult to under-report (M. Shaw, van Dijk, & Rhomberg, 2003). To aid analyses, the study period was split into five yearly periods (i.e., 1986–1990, 1991–1995, 1996–2000, and so forth). This was done for a number of reasons. First, census data were most often available in five-year periods. In fact, the census only started releasing yearly data starting 2000. In addition, this allowed for ease of analysis, and aided interpretation. Grouping the data also allowed greater consistency on time-frame availability for other variables used in the study such as the socio-demographic data and NDVI indicator, as outlined below. The cumulative homicide rate per 100,000 population was then calculated for each city across each five-year period by summing the annual homicide counts dividing by the population count for the most recent year in each of the five-year periods. This five-year cumulative homicide rate was used as the dependent variable.

Census data and spatial boundaries

Census data were used to compile seven socio-demographic variables that may confound the relationship between levels of city greenness and homicide. This was done for each city at each five-year interval as census data were mostly available in five-year periods[1]. We selected a number of variables that have previously been shown to be associated with crime at the city-level (Borg & Parker, 2001; Jensen, Gatrell, Boulton, & Harper, 2004; Li & Weng, 2007; McCarthy, Galle, & Zimmern, 1975; Messner & Sampson, 1991; Pozzi & Small, 2001; Szantoi, Escobedo, Wagner, Rodriguez, & Smith, 2012; Thaler, 1978). The variables selected are primarily informed by the well-known social disorganization theory of C. Shaw and McKay (1942) which posits that neighborhoods (or cities) with high levels of economic deprivation, racial heterogeneity, residential mobility, and family disruption experience more crime and disorder than other neighborhoods (or cities). We do emphasize, however, that this study is not a test of this theoretical framework. Rather, the emphasis here is on selecting theoretically-specified variables that have universally been found to be associated with increased crime risk in neighborhoods (or cities). We did initially consider selecting variables that may predict longitudinal patterns of homicide over 30 years but there was difficulty in obtaining and aligning the various predictors for each city at each time increment. Moreover, research has found similar structural predictors of crime over time in a variety of different contexts (Stansfield & Parker, 2013; Taylor, Groff, Elesh, & Johnson, 2014).

The variables selected include *population density* - which has previously been found to be positively associated with homicide (McCarthy et al., 1975) and has been used in studies examining the causes of crime over time (see Battin & Crowl (2017)). The impact of educational

[1] U.S. Census started to produce yearly data in 2000.

attainment on criminality has been extensively investigated with most research showing significant and important linkages between high school graduation and crime (Gottfredson, 1985; Lochner & Moretti, 2004). For this reason, the *percentage of persons without a high school degree* was included as a confounder in the study. Likewise, the association between employment and crime has been exhaustively investigated with researchers most often finding an inverse relationship using a range of different methods (Blokland & Nieuwbeerta, 2005; Crutchfield & Pitchford, 1997; Farrington, Gallagher, Morley, St. Ledger, & West, 1986; Sampson & Laub, 1993) although the mechanisms that account for this association generally remain poorly understood (Apel & Horney, 2017). Our in study we used the *percentage of population who were unemployed* to further investigate this linkage. The *percentage of single mother households* was included to address the issue of familial stability. According to social disorganization theory, an individual from a disrupted family is less likely to develop local friendship networks and a concomitant sense of connection with their neighborhood which can lead to neighborhood disintegration and crime. This variable – a common proxy for family disruption - has previously been found to be associated with crime across a diverse array of contexts in the United States (Messner & Sampson, 1991). Next, we compiled *percent of the population living in poverty* using the proportion of the population living below poverty as defined and compiled by the data for each city over each time-period. Poverty thresholds are defined by the United States Census Bureaus' American Community Survey (ACS) on a national scale and are updated annually for inflation using the Consumer Price Index for All Urban Consumers[2]**.** Poverty has previously been used in studies of this nature (Borg & Parker, 2001; Jensen et al., 2004; Thaler, 1978). The percentage of individuals aged between 15

[2] The first iteration of the ACS was in 2005. For the years preceding the ACS we used poverty thresholds as defined by the US Census' Summary Tape Files (see https://www.census.gov/data/datasets/1990/dec/summary-file-2.html as an example)

and 24 years is a sub-population often associated with higher crime (Steffensmeier, Allan, Harer, & Streifel, 1989). Young adults have consistently had the highest homicide offending rates compared to other age groups (Cooper & Smith, 2011). A *diversity index (DI)* (see Meyer & McIntosh (1992)) was finally calculated to provide a measure of racial and ethnic diversity across cities. The DI measures the probability that any two people chosen at random from a given city are of different races or ethnicities; and is measured on a scale of 0 to 1, with 0 indicating that a city is totally homogeneous and 1 stating a city is totally heterogeneous. The DI is frequently been employed in population studies (see Johnson & Lichter (2010); Tam & Bassett Jr (2004)) and is calculated as:

$$DI = 1 - \sum (p_i^2)$$

Where p_i is the proportion of White, Black or African-American, Hispanic or Latino, Asian and Native Hawaiian, and all other races (including two or more races), divided by the total population.

We are aware that it is not necessarily the mere presence of minority communities that impact crime risk but rather the social and economic marginalization affecting minority groups that may lead to higher crime (Krivo & Peterson, 2000; Peterson & Krivo, 2010). We believe however that the operationalization of risk related to racial/ethnic heterogeneity at the neighborhood level can best be measured using a diversity index which measures the level of 'differentness' specifically in neighborhoods. Research has exhaustively shown that the racial and/or ethnic composition of neighborhoods has an association with crime across a range of contexts using the measure we provide (Breetzke, 2020; Lum & Vovak, 2018; Wu & Lum, 2019).

Census data were obtained for the last year in each five-year period over the entire 30 years and used as time-varying confounders in our statistical modeling (detailed below). Intercensal data were not available for 1995, so we averaged the census data for 1990 and 2000 to generate estimates for this time period. For percentage single mother households, we calculated the number of households and those that involved single mothers for each census tract within each city boundary (as it was not provided at the city level). For census tracts that partially fell inside the city boundary, we calculated the percentage area within the city and weighted the number of single mother households using this percent area (i.e., if a census tract contained 100 single mother households and had 50% of its area within the city, 50 single mother households was the result). Thus, we totaled all single mother households and households to generate an overall percent single mother households for each city.

A number of cities had missing variables for certain time-periods[3]. For example, during the 2001-2005 time-period, almost nine per cent of cities were missing data pertaining to the percentage of population aged 16 years and older who were unemployed. For these variables, and others, we employed the Multiple Imputation by Chained Equations (MICE) method to impute these missing data (see White, Royston, & Wood, 2011). This method uses the distribution of the available data to generate estimates of plausible values for missing continuous and categorical data (Royston & White, 2011) and has been successfully used in previous research of this nature (Mars et al., 2014; Nutsford, Pearson, Kingham, & Reitsma, 2016; Sarkisian & Gerstel, 2015). In total, we generated nine replicates of the data through imputation.

City boundaries from the 2015 census year were used for analyses (U.S. Census Bureau, 2015). A number of cities were founded or changed during the course of the study period. For example, Centennial (in Colorado) was founded in 2001, so there was only data for the second half of the study period (2005–2015). Similarly, Louisville City (in Kentucky) became Louisville

[3] Missing data ranging from 1.72% to 8.62% (see Table 1). While unfortunate, this is simply a reality when undertaking longitudinal research across multiple cities using a large number of variables.

Metro in 2003. In the latter instance we used the data for Louisville City in the first half of the study period (1990–2000) and Louisville Metro for the second half of the study period (2005–2015).

Climate data

A final time-varying confounder added to the study was the temperature of each city. Over the past decade there has been a growing interest to determine how environmental factors such as climate influence different types of crime (see Breetzke & Cohn (2012); Ceccato (2005); Linning et al. (2017); Mares (2013); Schinasi & Hamra (2017). The vast majority of this research across a number of geographic locales has found positive associations between various meteorological parameters such as temperature, humidity, precipitation and crime (Agnew, 2011; Hipp, Curran, Bollen, & Bauer, 2004; Ranson, 2014). To control for the role that climate may play in the occurrence and risk of criminality in cities throughout the US, we compiled the mean annual temperature for all cities for each of the five-year periods using data from the PRISM Climate Group (PRISM Climate Group, 2018) and included this as a confounding variable in our analysis[4]. We used temperature rather than other meteorological parameters such as precipitation in our analysis for a number of reasons. First, historically most prior research examining the linkage between climate and crime use temperature as the main parameter of interest (Dexter, 1904; Gamble & Hess, 2012; Hu et al., 2017; Morrison, 1891; Rotton & Cohn, 2001, 2003; Stevens, Beggs, Graham, & Chang, 2019). Second, temperature has been identified as the most powerful meteorological variable when accounting for influences of violent crime trends globally (D. M. Mares & Moffett, 2015). Third, there is a rich theoretical framework that attempts to explain the

[4] There were no available yearly temperature data for the cities of Anchorage, Alaska and Honolulu, Hawaii. For these two cities, we used PRISM's 30-year normal data.

empirical association most often found between temperature and crime (see (Craig A. Anderson, 1989; C. A. Anderson & Bushman, 2002; Baron & Bell, 1976; Zillmann, 1983). Using temperature, therefore, allows us to contrast the results of this work with past theory and research.

In truth, a range of additional confounding socio-demographic and meteorological variables could have been added to our analysis. We were weary, however, of detracting from the original aim of this study, which is to examine the impact of city greenness on homicide and not to empirically test the impact of various socio-demographic and climatic variables on crime. We ultimately felt that this list of variables we identified best provided an overall level of risk of crime in cities throughout the US and therefore acted as controls in our analysis.

City greenness data

The level of greenness for each city was determined using the remote sensing-based normalized difference vegetation index (NDVI):

$$NDVI = \frac{Near\ Infrared - Red}{Near\ Infrared + Red}$$

The relatively well-known NDVI has proven to be a valid and efficient indicator of ground-based neighborhood and city-level greenness in previous studies of this nature (Rhew, Vander Stoep, Kearney, Smith, & Dunbar, 2011; Wicherts et al., 2014; Zhou, Troy, Morgan Grove, & Jenkins, 2009). In this research, we used Landsat 5 and 7 annual greenest-pixel TOA (Top-Of-Atmosphere) reflectance composites with a spatial resolution of 30-m to calculate city-level greenness for all 290 major cities. Each pixel in the grids represent the highest NDVI value of the entire year when the vegetation is at its peak (values range from 0 (low) to 1 (high) greenness, grand mean for all cities over 30 years = 0.42). We chose coverages for 1990, 1995, 2000, 2005, 2010, and 2015 in order to align with our demographic and climatic controls and then calculated the city-level mean

NDVI values for each of these years, to represent a value for the five-year period. Thus, each city in the study had six measures of average greenness (see Table S1). Table 1 shows the variables used in this study at each aggregated five-year increment. This variable served as our independent variables of interest in our statistical analyses, which we re-scaled by 100 for regression analyses to make findings more easily interpretable.

Statistical analyses

A number of steps were undertaken in our analyses. First, we calculated the mean and standard deviation of homicide and all covariates for each city. We then grouped the cities into nine regions based on US Census divisions (U.S. Census Bureau, 2018) as regions may have similar vegetation types and climates (e.g., the central plains). Similar regional groupings were also utilized by the UCR, and thus, allowed for consistency in our study. Finally, we fitted a multilevel conditional growth curve model to examine the trajectories of homicide over time, accounting for clustering within each region.

Growth curve modeling is a broad term for statistical models which account for repeated measures and, when multilevel, allow for estimations of inter-individual/unit variability in intra-individual/unit patterns of change over time (Curran, Obeidat, & Losardo, 2010). Other traditional measures of analyzing longitudinal data (e.g. repeated measures analysis of variance, multivariate analysis of variance, raw and residual changes) focus over units (here, the unit is a city) within time-points. Growth curve models, on the other hand, look over time-points within a given unit (or city)**.** Thus, each city's trajectory is estimated based on the data available for that city, resulting in an intercept and growth term for each city**.** In addition, growth curve models are highly flexible in including partially missing data and time-varying covariates (predictors that vary over time)

(Curran et al., 2010), which characterized the data sets we used in this study. Moreover, they have much higher levels of statistical power compared to traditional methods applied to the same data (Muthén & Curran, 1997).

Growth curve models estimate the unique trajectories in the outcome (in our study, this is homicide rate) observed over time for each unit (or city), while accounting for independent variables. The collection of these individual trajectories in the outcome over time is a result of the model's fixed and random effects (Curran et al., 2010). Fixed effects estimate the mean intercept (i.e., starting point) and mean slope (i.e., rate of change) of the pooled trajectories of all the observations (cities). In other words, the fixed effects in the growth model represent the mean trajectory of homicide rate from the pooling of all the cities. The random effects, on the other hand, estimate the between-city variability in the city intercepts and slopes and represent the variance of the individual city trajectory around the mean. Thus, larger random effects mean greater variances of intercepts and slopes compared to the mean values. A conditional growth model includes one or more independent predictors of growth, which in our case are time-varying covariates (greenness, census variables, and temperature). By adding these time-varying covariates in our model, we were able to estimate their influence to the repeated measures of homicide rate. In a regression model, residuals measure the random unexplained variability against the "best-fit" line (distance between the data point and the regression line). In a conditional growth curve model, however, the residuals contain the random variability plus the effects of the time-varying covariates. Thus, the repeated measure (homicide rate) is jointly determined by both growth factors (e.g. intercept, slope) and the time-varying covariates at a specified time. Likewise, we further expand our model to include interactions between time-varying covariates and time to assess the difference in the magnitude of the time-varying covariates effect as a function of time.

Specifically, we fitted a multilevel conditional linear growth curve model to investigate the effects of the changes in city greenness on the changes in homicide rate over time, controlling for time-varying socio-demographic and climatic covariates using the formula:

$$Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \cdots + \beta_9 X_{9ij} + u_i + v_i + w_j$$

Where:

Y = Homicide rate indexed by the five-year period (i) and city (j)

X_1 to X_9 = The nine covariates used in this study indexed by the five-year period (i) and city (j)

u_i = random intercept for the city through each five-year period (i)

v_i = random intercept for the region through each five-year period (i)

w_j = random intercept for each five-year period in a different city (j)

We used homicide rate as the outcome of the model and specified the model's fixed effects to include all the time-varying covariates (variables X_1 to X_9). We included random effects for three levels in our data: each city measured by five-year period, region measured by five-year period, and the five-year period. These random effects were included as we have multiple observations for each city over time and to account for city clustering within each region. Yearly effects are approximated in the five-year summary period.

We quantified the extent of multicollinearity in our model using the variance inflation factor (VIF) and also tested for the homogeneity of variance (homoscedasticity). Finally, we compare beta coefficients to examine the direction of effects for all covariates on homicide. All analyses were undertaken using R.

Results

Descriptive

The five-year period trends for homicide rate, average greenness, and other covariates are presented in Table 1. Overall, the homicide rate increased from 1990 to 1995 (from 52.1 to 60.8 deaths per 100,000 population) then gradually declined to 33.5 deaths per 100,000 population in 2015. The average greenness slightly increased from 0.41 in 1990 to 0.43 in 2015. Population density steadily increased from 3,100 people per square mile in 1990 to 3,900 people per square mile in 2015. The percentage of males aged 15 to 24 years decreased marginally over the study period (16% in 1990 to 15% in 2015) while the percentage of the population aged 25 years and older without any diploma encouragingly decreased from 23% in 1990 to 14% in 2015. The percentage of the population aged 16 years and older who were unemployed increased from four percent in 1990 to eight percent in 2010, then decreased to five percent in 2015. The average percentage of single mother households varied greatly across the study period with an increase of almost 32% from 1990 to 2005 (from 20% to 52%) followed by a decline to 23% in 2015. Ethnic diversity index gradually increased from 1990 to 2015 (0.42 to 0.57). Mean annual temperature remained almost constant within the entire study period**.**

Unsurprisingly, there was wide variability in the changes in homicide rates in US cities across the 30-year study period (see Figure 1). Overall, homicide rates declined in 218 out of the 290 cities (75%) with most of the cities in the Pacific, Mountain, West South Central, East South Central, South Atlantic, and New England regions exhibiting declining homicide rates. The largest declines in homicide were observed in Washington, DC, Atlanta (Georgia), and Richmond (Virginia) while the largest increases in homicide were in Pittsburgh (Pennsylvania), Salinas (California), and Baton Rouge (Louisiana). On average, the East South Central region had the highest homicide rate with 77 deaths per 100,000 population, while the Mountain region had the lowest homicide rate with 25 deaths per 100,000 population (see Table S2).A wide variation was also found in the average greenness of US cities, however, unlike homicide, average city greenness generally increased across the 30-year study period (see Figure 2). The majority of the cities showed a slight increase in average greenness although the increase was marginal with 156 cities (54%), increasing by less than 0.05 NDVI. On the other hand, 87 cities (30%) experienced a decrease in average greenness of less than 0.05 NDVI. Most of the cities in the Pacific, West South Central, South Atlantic, East North Central, and New England regions showed an increase in the average greenness from the 1980s compared to 2010s. The three cities with the highest increase in average greenness were Anchorage (Alaska), Honolulu (Hawaii), and Brownsville (Texas) while the three cities with the biggest decline in average greenness were Gilbert (Arizona), Chandler (Arizona), and Fargo (North Dakota).

Inferential

We found that average city greenness had a significant negative relationship with the trajectories of homicide ($\beta = -0.30$, 95% CI – 0.55, – 0.05, *p*-value = 0.017), after controlling for various time-varying demographic and climatic variables (see Table 2). For every 0.01 unit change in average greenness (NDVI), we would expect 0.30 fewer deaths per 100,000 population. The percentage of the population 25 years and older with no diploma, the population below poverty line, and ethnic diversity index all showed significant, positive relationships with homicide rate ($\beta = 0.84$; $p < 0.001$; $\beta = 1.04$; $p < 0.001$; $\beta = 55.65$; $p < 0.001$, respectively). Population density, population of people aged 25-24y, the percentage of the population aged 16 years and older who are unemployed, the percentage of single-mother households, and mean annual temperature did not exhibit any significant relationships (Table 2). According to the VIFs reported in Table 2, all values were < 4 and thus multi-collinearity was not deemed to be an issue (Hair, Black, Babin, & Anderson, 2010). The greatest variability in homicide rate trajectories was found between cities (ICC = 0.80). The correlations in observations within year and within region were modest (ICC = 0.41 & 0.33, respectively).

Discussion

The initial results of our study showed a decline in homicide rates over a 30-year period across the large majority of the United States. This trend is congruent with past research which has shown a drop in crime rates internationally; the so-called 'crime drop' (see Farrell (2013); Knepper (2012); van Dijk et al. (2012)). The notion here is that crime has significantly declined in most advanced countries over the past two decades, a consequence of improved and more security (see Farrell (2013). Additional reasons for the decline include increased levels of incarceration (Levitt, 1996), the economy (as measured by consumer sentiment) (Rosenfeld & Fornango, 2007), changing demographics (Blumstein & Rosenfeld, 2008), and other improvements made in policing (Farrell, 2016). We also found an overall increase in the urban greenness in cities across the US although this was admittedly slight. Of note, the largest increase in greenness was observed in the most northern US city included in this study, Anchorage, Alaska. This polar city has seen tremendous change in the length of the growing season (increase of 1.9 days per decade, see (Lader, Walsh, Bhatt, & Bieniek, 2018) and the amount of greenery, largely due to increasing land temperatures over this time period . Also of note, the largest decline in greenness was observed in two cities in Arizona, a state with severe water scarcity, decreasing rainfall, and prolonged drought, related to climate change (Scott & Lutz-Ley, 2016). These findings suggest that while some cities may actively promote greenness, climate change may play a larger role in the trajectories of greenness across US (and global) cities into the future (Schut, Ivits, Conijn, Ten Brink, & Fensholt, 2015). The intraclass correlation coefficient for cities was above 0.80, indicating that within-city values were highly correlated. This suggests that high (or low) homicide rates in cities tend to be maintained at high (or low) levels. While greenness may have a small impact, much of the variability in homicide rate is at the city-level. Similarly, the intraclass correlations for year and region were 0.38 and 0.37, respectively, which indicates that homicide values were similar within years and regions. While it is notable that these ICCs are relatively high, investigating the causes behind these values or in-depth regional analyses of the relationship between greenness and homicide are beyond the scope of the current study and warrant further exploration.

Regarding the substantive aim of this research, we found that the increase in city greenness significantly predicts the declining trajectory of homicide rate over time suggesting that the increased greening of cities witnessed over the past 30 years in the US may be used, in part, to explain the reduction in homicide in a number of cities. It is difficult to compare the results of our work to prior research given that this is, to our knowledge, the first study that has examined the association between city greenness and homicide over a number of decades and tested this relationship across many cities. Indeed, previous research has largely focused on measuring this association as the city level (Donovan & Prestemon, 2012; Garvin et al., 2013) and/or using cross-sectional methods (Snelgrove et al., 2004; Troy et al., 2012). The limited number of longitudinal studies that have been undertaken have most often found a reduction in crime over time after a greening initiative (Branas et al., 2011; Branas et al., 2018; Burley, 2018; Garvin et al., 2013; B. Harris et al., 2018; Sadler et al., 2017). These examples provide some initial evidence of the potential for added greenness to contribute to reductions in crime they are most often context-specific reducing their generalizability to other cities.

Of course, there are a number of limitations to consider in this work. First, the study focused on the amount of greenness within cities and its association with homicide and did not consider the quality of greenness (e.g., aesthetics, native versus invasive), nor the differences in vegetation types across cities, as well as the accessibility and usage of green areas. It is being increasingly acknowledged that the type and frequency of greenspace interactions can impact health and wellbeing rather than greenness simply being available (for a few examples of studies evaluating quality and usage differences, see Holt et al. (2019), White et al. (2019), Liu et al. (2018), Fuller et al. (2007). As a result, our study is not able to draw causal inferences due to the lack of experimental manipulation. Regarding the type of greenness, a number of US cities, such as those in the post-industrial Rust Belt, have seen an increase in the number of vacant lots during this period. These lots often have overgrown vegetation that may **inadvertently** promote crime (Goldstein, Jensen, & Reiskin, 2001), but also positively contribute to a city's mean NDVI. Regarding the former, there is currently a wealth of evidence that indicates that greenness can actually increase the risk of crime (see (Boessen & Hipp, 2018; Demeau & Parent, 2018; Groff & McCord, 2012; Kimpton et al., 2017)) although research findings are inconsistent (Pearson et al., 2020) and the majority of this research has focused on parks (as one measure of greenness) and the areas adjacent to them. Researchers have also noted that the quality and characteristics of 'greenspaces' as well as the social composition of the surrounding neighborhoods seem to have a mediating effect on the greenspace-crime relationship (Grommon, McCluskey, & Bynum, 2017; Mary K Wolfe & Jeremy Mennis, 2012). Greenspace quality, in this instance, refers to the level of greenness or diversity of vegetation, the maintenance of greenspace structures and amenities, as well as the inclusion of safety features such as lighting (Sadler et al., 2017). Experimental research has shown that improvements in the quality of these greenspaces, in fact, lowers crime (Beam, Szabo, Olson, Hoffman, & Beyer, 2020). As Kimpton et al. (2017, p. 304) note: "…as greenspaces are morphologically distinct, their ability to generate crime is arguably also distinct".

Second, measuring mean NDVI over time does not indicate whether the change in greenness were caused by varying seasons of drought/rainfall, new 'green' infrastructure (e.g., median trees, parks, green roofs), vacant lots reverting to nature, or intentional greening initiatives undertaken in neighborhoods and cities. Third, aggregation to cities may hide heterogeneity within cities. Previous research has shown that lower socioeconomic status residents have less exposure to trees (Greene, Robinson, & Millward, 2018) which suggests that city-level greenness is not uniformly experienced by all residents of a city. Future work could usefully examine these nuances of greenness to provide further information about the potential to improve health and quality of life in cities. Confirmation of this study's findings in other global cities would provide more robust conclusions about the crime-reduction potential of city greening efforts, with potential implications for climate-related vegetation change mitigation.

A fourth limitation is the use of UCR as a source of homicide data. Using UCR data to measure crime has well-known limitations (see (Walsh, 2011; Walsh & Jorgensen, 2017) For example, UCR reporting is voluntary with approximately four percent of the population (12.5 million) not included in the data. Despite this however previous research has shown that using official police data usually produces results consistent with victimization surveys (see (Byrne & Sampson, 1986; McDowall & Loftin, 1992). Relatedly, there are also a number of other factors at the population level that can impact crime trends and reporting. For example, medical advancements since the 1980s have resulted in a reduction in the number of homicides due to improved care but a concomitant increase in the number of attempted homicides (Harris, Thomas, Fisher, & Hirsch, 2002). It is difficult to control for this in our study given the number of cities and the time period under investigation. Finally, crime trend data could possibly shift based on the selected range of dates. As a result, choosing a different starting or ending year could result in a different trend observed and impact the results. We are reasonably satisfied however that the homicide data we have extracted and employ in this study is a relatively accurate representation of the true magnitude and distribution of this crime type throughout the country. Moreover, records from the UCR represent the most official and spatially replete crime dataset available in the country. Finally, our study was limited to major cities across the US with populations over 100,000. It could be that the findings of our research are not applicable to smaller cities throughout the country. There is some evidence that the size of cities can influence the protective benefits of greenness on general health and wellbeing (see (James et al., 2015) which makes this an important avenue for future work.

Conclusion

In this study, we observed that urban greenness had a small negative impact on homicide rates in the United States, suggesting that greening efforts in cities may reduce violent crimes. While this finding is supported by much prior research across the United States (Hu et al., 2017; D. Mares, 2013; Ranson, 2014), the results of our work are based on an analysis of 290 cities across a 30-year time period in the country, which, to our knowledge, has never been carried out previously. While there was some variation between regions, the overarching finding was that increased greenness negatively impacts homicide across a broad swathe of the United States. This finding has important implications for human and urban design responses to climate change as it suggests that changes in greenness may impact criminal behavior. With climate change predicted to result in a decreased global level of greenness in some regions (Eskandari et al., 2016; Webb et al., 2017), there is an urgent need therefore to 'green' cities, both for health promotion and crime mitigation reasons. Indeed, with increasing evidence suggesting that changes in climatic factors have already indirectly impacted changes in landscape greenness in the US over the past 25 years (Nash, Wickham, Christensen, & Wade, 2017), the need for large-scale interventions is now.

Perhaps the most obvious approach that can be adopted to deter criminal behavior based on the results of our research could be employing crime prevention through environmental design (CPTED) principles in city re-design and re-development. This approach refers to the notion that physical space can be designed to maximize the crime prevention potential of an area. It then involves the development of physical designs that reduce the opportunity for crime to occur. While various localized 'greening' CPTED initiatives have been undertaken in the United States with reasonable success (see (Beam et al., 2020; Branas et al., 2011; M. Kondo et al., 2016), there is a need for increased uptake of these initiatives nationally and, at least initially, in cities of greatest concern. Failure to do so may result in a small, but meaningful increases in violent crime for decades into the future.

References

Agnew, R. (2011). Dire forecast: A theoretical model of the impact of climate change on crime. *Theoretical Criminology, 16*(1), 21–42. doi:10.1177/1362480611416843

Anderson, C. A. (1989). Temperature and aggression: Ubiquitous effects of heat on occurrence of human violence. *Psychological Bulletin, 106*(1), 74–96. doi:10.1037/0033-2909.106.1.74

Anderson, C. A., & Bushman, B. J. (2002). Human aggression. *Annual Review of Psychology, 53*, 27–51. doi:10.1146/annurev.psych.53.100901.135231

Apel, R., & Horney, J. (2017). How and why does work matter? Employment conditions, routine activities, and crime among adult male offenders. *Criminology, 55*(2), 307–343. doi:10.1111/1745-9125.12134

Baron, R. A., & Bell, P. A. (1976). Aggression and heat: The influence of ambient temperature, negative affect, and a cooling drink on physical aggression. *Journal of Personality and Social Psychology, 33*(3), 245–255. doi:10.1037//0022-3514.33.3.245

Battin, J. R., & Crowl, J. N. (2017). Urban sprawl, population density, and crime: An examination of contemporary migration trends and crime in suburban and rural neighborhoods. *Crime Prevention and Community Safety, 19*(2), 136–150. doi:10.1057/s41300-017-0020-9

Beam, D. R., Szabo, A., Olson, J., Hoffman, L., & Beyer, K. M. M. (2020). Vacant lot to community garden conversion and crime in Milwaukee: A difference-in-differences analysis. *Injury Prevention: Journal of the International Society for Child and Adolescent Injury Prevention*.

Berman, M. G., Jonides, J., & Kaplan, S. A. (2008). The cognitive benefits of interacting with nature. *Psychological Science, 19*(12), 1207-1212.

Berto, R. (2005). Exposure to restorative environments helps restore attentional capacity. *Journal of Environmental Psychology, 25*(3), 249–259. doi:10.1016/j.jenvp.2005.07.001

Blokland, A. A. J., & Nieuwbeerta, P. (2005). The effects of life circumstances on longitudinal trajectories of offending. *Criminology, 43*, 1203–1240. doi:10.1111/j.1745-9125.2005.00037.x

Blumstein, A., & Rosenfeld, R. (2008). Factors contributing to US crime trends. In G. A. & R. Rosenfeld (Eds.), *Understanding Crime Trends: Workshop Report* (pp. 13–44). Washington, DC: National Academies Press.

Boessen, A., & Hipp, J. R. (2018). Parks as crime inhibitors or generators: Examining parks and the role of their nearby context. *Social Science Research, 76*, 186–201. doi:10.1016/j.ssresearch.2018.08.008

Borg, M. J., & Parker, K. F. (2001). Mobilizing law in urban areas: The social structure of homicide clearance rates. *Law and Society Review, 35*(2), 435–466. doi:10.2307/3185409

Bowler, D. E., Buyung-Ali, L. M., Knight, T. M., & Pullin, A. S. (2010). A systematic review of evidence for the added benefits to health of exposure to natural environments. *BMC Public Health, 10*, 456. doi:10.1186/1471-2458-10-456

Boyko, C. T., & Cooper, R. (2014). Density and mental wellbeing. In *Wellbeing: A Complete Reference Guide* (pp. 1–22): John Wiley & Sons, Ltd.

Branas, C. C., Cheney, R. A., MacDonald, J. M., Tam, V. W., Jackson, T. D., & Ten Have, T. R. (2011). A difference-in-differences analysis of health, safety, and greening vacant urban space. *American Journal of Epidemiology, 174*(11), 1296–1306. doi:10.1093/aje/kwr273

Branas, C. C., South, E., Kondo, M. C., Hohl, B. C., Bourgois, P., Wiebe, D. J., & MacDonald, J. M. (2018). Citywide cluster randomized trial to restore blighted vacant land and its effects on violence, crime, and fear. *Proceedings of the National Academy of Sciences, 115*(12), 2946–2951. doi:10.1073/pnas.1718503115

Brantingham, P. L., & Brantingham, P. J. (1993). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology, 13*, 3–28.

Bratman, G. N., Daily, G. C., Levy, B. J., & Gross, J. J. (2015). The benefits of nature experience: Improved affect and cognition. *Landscape and Urban Planning, 138*, 41–50. doi:10.1016/j.landurbplan.2015.02.005

Bratman, G. N., Hamilton, J. P., Hahn, K. S., Daily, G. C., & Gross, J. J. (2015). Nature experience reduces rumination and subgenual prefrontal cortex activation. *Proceedings of the National Academy of Sciences, 112*(28), 8567–8572. doi:10.1073/pnas.1510459112

Breetzke, G. D. (2020). The importance of space and time in aggravated assault victimization. *Journal of Interpersonal Violence, 35*(13-14), 2536–2557.

Breetzke, G. D., & Cohn, E. G. (2012). Seasonal assault and neighborhood deprivation in South Africa. *Environment and Behavior, 44*(5), 641–667. doi:10.1177/0013916510397758

Burley, B. A. (2018). Green infrastructure and violence: Do new street trees mitigate violent crime? *Health & Place, 54*, 43–49. doi:10.1016/j.healthplace.2018.08.015

Byrne, J. M., & Sampson, R. J. (1986). Key issues in the social ecology of crime. In J. M. Byrne & R. J. Sampson (Eds.), *The Social Ecology of Crime* (pp. 1–22). New York: Springer-Verlag.

Ceccato, V. (2005). Homicide in São Paulo, Brazil: Assessing spatial-temporal and weather variations. *Journal of Environmental Psychology, 25*(3), 307–321. doi:10.1016/j.jenvp.2005.07.002

Cooper, A., & Smith, E. L. (2011). *Homicide trends in the United States, 1980–2008: Annual rates for 2009 and 2010*. Retrieved from https://www.bjs.gov/content/pub/pdf/htus8008.pdf

Crutchfield, R. D., & Pitchford, S. R. (1997). Work and crime: The effects of labor stratification. *Social Forces, 76*(1), 93–118. doi:10.1093/sf/76.1.93

Curran, P. J., Obeidat, K., & Losardo, D. (2010). Twelve frequently asked questions about growth curve modeling. *Journal of Cognition and Development, 11*(2), 121–136. doi:10.1080/15248371003699969

Demeau, E., & Parent, G. (2018). Impacts of crime attractors and generators on criminality in Montreal. *Canadian Journal of Criminology and Criminal Justice, 60*(3), 387–412. doi:10.3138/cjccj.2017-0028.r1

Dexter, E. G. (1904). *Weather influences; An empirical study of the mental and physiological effects of definite meteorological conditions*. London: The Macmillan Company.

Donovan, G. H., & Prestemon, J. P. (2012). The effect of trees on crime in Portland, Oregon. *Environment and Behavior, 44*(1), 3–30. doi:10.1177/0013916510383238

Edmonds, J. A., & Rosenberg, N. J. (2005). Climate change impacts for the Conterminous USA: An integrated assessment summary. *Climate Change, 69*(151–162). doi:10.1007/s10584-005-3613-8

Eskandari, H., Borji, M., Khosravi, H., & Mesbahzadeh, T. (2016). Desertification of forest, range and desert in Tehran province, affected by climate change. *Solid Earth, 7*(3), 905–915. doi:10.5194/se-7-905-2016

Farrell, G. (2013). Five tests for a theory of the crime drop. *Crime Science, 2*(5). doi:10.1186/2193-7680-2-5

Farrell, G. (2016). Attempted crime and the crime drop. *International Criminal Justice Review, 26*(1), 21–30. doi:10.1177/1057567715615392

Farrington, D. P., Gallagher, B., Morley, L., St. Ledger, R. J., & West, D. J. (1986). Unemployment, school leaving, and crime. *British Journal of Criminology, 26*(4), 335–356. doi:10.1093/oxfordjournals.bjc.a047626

Federal Bureau of Investigation. (2018). UCR Technical Specifications, User Manuals, and Data Tools.

Fuller, R. A., Irvine, K. N., Devine-Wright, P., Warren, P. H., & Gaston, K. J. (2007). Psychological benefits of greenspace increase with biodiversity. *Biological Letters, 3*(4), 390–394. doi:10.1098/rsbl.2007.0149

Gamble, J. L., & Hess, J. J. (2012). Temperature and violent crime in dallas, Texas: Relationships and implications of climate change. *Western Journal of Emergency Medicine, 13*(3), 239–246. doi:10.5811/westjem.2012.3.11746

Garvin, E. C., Cannuscio, C. C., & Branas, C. C. (2013). Greening vacant lots to reduce violent crime: A randomised controlled trial. *Injury Prevention, 19*(3), 198–203. doi:10.1136/injuryprev-2012-040439

Goldstein, J., Jensen, M., & Reiskin, E. (2001). *Urban vacant land redevelopment: Challenges and progress*. Cambridge, MA: Lincoln Institute of Land Policy Working Paper.

Gottfredson, D. C. (1985). Youth employment, crime, and schooling: A longitudinal study of a national sample. *Developmental Psychology, 21*(3), 419–432. doi:10.1037/0012-1649.21.3.419

Greene, C. S., Robinson, P. J., & Millward, A. A. (2018). Canopy of advantage: Who benefits most from city trees? *Journal of Environmental Management, 208*, 24–35. doi:10.1016/j.jenvman.2017.12.015

Groff, E., & McCord, E. S. (2012). The role of neighborhood parks as crime generators. *Security Journal, 25*(1), 1–24. doi:10.1057/sj.2011.1

Grommon, E., McCluskey, J. D., & Bynum, T. S. (2017). From Theory to Practice: Reducing Gun Violence and Homicide in Detroit. In F. Brookman, E. R. Maguire, & M. Maguire (Eds.), *The Handbook of Homicide*: Wiley-Blackwell.

Hair, J., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Upper Saddle River, New Jersey: Pearson Education International.

Harris, A. R., Thomas, S. H., Fisher, G. A., & Hirsch, D. J. (2002). Murder and medicine: The lethality of criminal assault 1960-1999. *Homicide Studies, 6*(2), 128–166. doi:10.1177/108876790200600203

Harris, B., Larson, L., & Ogletree, S. (2018). Different views from the 606: Examining the impacts of an urban greenway on crime in Chicago. *Environment and Behavior, 50*(1), 56–85. doi:10.1177/0149206313478188

Hipp, J. R., Curran, P. J., Bollen, K. A., & Bauer, D. J. (2004). Crimes of opportunity or crimes of emotion? Testing two explanations of seasonal change in crime. *Social Forces, 82*(4), 1333–1372. doi:10.1353/sof.2004.0074

Holt, E. W., Lombard, Q. K., Best, N., Smiley-Smith, S., & Quinn, J. E. (2019). Active and passive use of green space, health, and well-being amongst university students. *International Journal of Environmental Research and Public Health, 16*(3). doi:10.3390/ijerph16030424

Hu, X., Wu, J., Chen, P., Sun, T., & Li, D. (2017). Impact of climate variability and change on crime rates in Tangshan, China. *Science of the Total Environment, 609*, 1041–1048. doi:10.1016/j.scitotenv.2017.07.163

Jacobs, J. (1961). *The death and life of great American cities*. New York: Vintage Books.

James, P., Banay, R. F., Hart, J. E., & Laden, F. (2015). A review of the health benefits of greenness. *Current Epidemiology Reports, 2*(2), 131–142. doi:10.1007/s40471-015-0043-7

Jensen, R., Gatrell, J., Boulton, J., & Harper, B. (2004). Using remote sensing and GIS to study urban quality of life and urban forest amenities. *Ecology and Society, 9*(5), 5.

Jiang, B., Deal, B., Pan, H., Larsen, L., Hsieh, C.-H., Chang, C.-Y., & Sullivan, W. C. (2017). Remotely-sensed imagery vs. eye-level photography: Evaluating associations among measurements of tree cover density. *Landscape and Urban Planning, 157*, 270–281. doi:10.1016/j.landurbplan.2016.07.010

Johnson, K. M., & Lichter, D. T. (2010). Growing diversity among America's children and youth: Spatial and temporal dimensions. *Population And Development Review, 36*, 151–175. doi:10.1111/j.1728-4457.2010.00322.x

Kaplan, R., & Kaplan, S. (1989). *The experience of nature: A psychological perspective*. New York: Cambridge University Press.

Kimpton, A., Corcoran, J., & Wickes, R. (2017). Greenspace and crime: An analysis of greenspace types, neighboring composition, and the temporal dimensions of crime. *Journal of Research in Crime and Delinquency, 54*(3), 303–337. doi:10.1177/0022427816666309

Knepper, P. (2012). An international crime decline: Lessons for social welfare crime policy? *Social Policy & Administration, 46*(4), 359–376. doi:10.1111/j.1467-9515.2012.00838.x

Knutsson, J. (1997). Restoring public order in a city park. In R. Homel (Ed.), *Policing for Prevention: Reducing Crime, Public Intoxication and Injury, Vol. 7* (pp. 133–151). New York: Willow Tree Press.

Kondo, M., Hohl, B., Han, S., & Branas, C. (2016). Effects of greening and community reuse of vacant lots on crime. *Urban Studies, 53*(15), 3279–3295. doi:10.1177/0042098015608058

Kondo, M. C., South, E. C., Branas, C. C., Richmond, T. S., & Wiebe, D. J. (2017). The association between urban tree cover and gun assault: A case-control and case-crossover study. *American Journal of Epidemiology, 186*(3), 289–296. doi:10.1093/aje/kwx096

Kong, D., Zhang, Q., Singh, V. P., & Shi, P. (2017). Seasonal vegetation response to climate change in the Northern Hemisphere (1982–2013). *Global and Planetary Change, 148*, 1–8. doi:10.1016/j.gloplacha.2016.10.020

Krivo, L. J., & Peterson, R. D. (2000). The structural context of homicide: Accounting for racial differences in process. *American Sociological Review, 65*, 547–559.

Kuo, F. E., & Sullivan, W. C. (2001a). Aggression and violence in the inner city: Effects of environment via mental fatigue. *Environment and Behavior, 33*(4), 543–571. doi:10.1177/00139160121973124

Kuo, F. E., & Sullivan, W. C. (2001b). Environment and crime in the inner city: Does vegetation reduce crime? *Environment and Behavior, 33*(3), 343–367. doi:10.1177/0013916501333002

Lader, R., Walsh, J. E., Bhatt, U. S., & Bieniek, P. A. (2018). Agro-climate projections for a warming Alaska. *Earth Interactions, 22*(18), 1–24. doi:10.1175/ei-d-17-0036.1

Landauer, M., Juhola, S., & Klein, J. (2018). The role of scale in integrating climate change adaptation and mitigation in cities. *Journal of Environmental Planning and Management, 62*(5), 741–765. doi:10.1080/09640568.2018.1430022

Lederbogen, F., Kirsch, P., Haddad, L., Streit, F., Tost, H., Schuch, P., . . . Meyer-Lindenberg, A. (2011). City living and urban upbringing affect neural social stress processing in humans. *Nature, 474*(7352), 498–501. doi:10.1038/nature10190

Levitt, S. D. (1996). The effect of prison population size on crime rates: Evidence from prison overcrowding litigation. *The Quarterly Journal of Economics, 111*(2), 319–351.

Li, G., & Weng, Q. (2007). Measuring the quality of life in city of Indianapolis by integration of remote sensing and census data. *International Journal of Remote Sensing, 28*(2), 249–267. doi:10.1080/01431160600735624

Linning, S. J., Andresen, M. A., & Brantingham, P. J. (2017). Crime seasonality: Examining the temporal fluctuations of property crime in cities with varying climates. *International Journal of Offender Therapy and Comparative Criminology, 61*(16), 1866–1891. doi:10.1177/0306624X16632259

Liu, Q., Zhang, Y., Lin, Y., You, D., Zhang, W., Huang, Q., . . . Lan, S. (2018). The relationship between self-rated naturalness of university green space and students' restoration and health. *Urban Forestry & Urban Greening, 34*, 259-268. doi:https://doi.org/10.1016/j.ufug.2018.07.008

Lochner, L., & Moretti, E. (2004). The effect of education on crime: Evidence from prison inmates, arrests, and self-reports. *American Economic Review, 94*(1), 155–189. doi:10.1257/000282804322970751

Longcore, T., & Rich, C. (2004). Ecological light pollution. *Frontiers in Ecology and the Environment, 2*(4), 191–198. doi:10.1890/1540-9295(2004)002[0191:ELP]2.0.CO;2

Lum, C., & Vovak, H. (2018). Variability in the use of misdemeanor arrests by police agencies from 1990 to 2013: An application of group-based trajectory modeling. *Criminal Justice Policy Review, 29*(6-7), 536–560.

Mares, D. (2013). Climate change and crime: monthly temperature and precipitation anomalies and crime rates in St. Louis, MO 1990–2009. *Crime, Law and Social Change, 59*(2), 185–208. doi:10.1007/s10611-013-9411-8

Mares, D. M., & Moffett, K. W. (2015). Climate change and interpersonal violence: A "global" estimate and regional inequities. *Climatic Change, 135*(2), 297–310. doi:10.1007/s10584-015-1566-0

Mars, B., Heron, J., Crane, C., Hawton, K., Lewis, G., Macleod, J., . . . Gunnell, D. (2014). Clinical and social outcomes of adolescent self harm: Population based birth cohort study. *BMJ, 349*, g5954. doi:10.1136/bmj.g5954

McCarthy, J. D., Galle, O. R., & Zimmern, W. (1975). Population density, social structure, and interpersonal violence: An intermetropolitan test of competing models. *American Behavioral Scientist, 18*(6), 771–791. doi:10.1177/000276427501800604

McDowall, D., & Loftin, C. (1992). Comparing the UCR and NCS over time. *Criminology, 30*, 155–132. doi:10.1111/j.1745-9125.1992.tb01097.x

Messner, S. F., & Sampson, R. J. (1991). The sex ratio, family disruption, and rates of violent crime: The paradox of demographic structure. *Social Forces, 69*(3), 693–713. doi:10.2307/2579470

Meyer, P., & McIntosh, S. (1992). The USA Today index of ethnic diversity. *International Journal of Public Opinion Research, 4*(1), 56–58. doi:10.1093/ijpor/4.1.51

Morrison, W. D. (1891). *Crime and its causes*. London: Swan Sonnenschein & Co.

Muthén, B. O., & Curran, P. (1997). General longitudinal modeling of individual differences in experimental designs: A latent variable framework for analysis and power estimation. *Psychological Methods, 2*, 371–402. doi:10.1037/1082-989X.2.4.371

Nash, M. S., Wickham, J., Christensen, J., & Wade, T. (2017). Changes in landscape greenness and climatic factors over 25 years (1989–2013) in the USA. *Remote Sensing, 9*(3), 295. doi:10.3390/rs9030295

Nutsford, D., Pearson, A. L., Kingham, S., & Reitsma, F. (2016). Residential exposure to visible blue space (but not green space) associated with lower psychological distress in a capital city. *Health & Place, 39*, 70–78. doi:10.1016/j.healthplace.2016.03.002

Office for Victims of Crime. (2017). *National crime victims' rights week resource guide: Crime and victimization fact sheets*. Retrieved from https://ovc.ncjrs.gov/ncvrw2017/images/en_artwork/Fact_Sheets/2017NCVRW_UrbanRural_508.pdf

Pearson, A. L., Pfeiffer, K. A., Gardiner, J., Horton, T., Buxton, R. T., Hunter, R. F., . . . McDade, T. (2020). Study of active neighborhoods in Detroit (StAND): Study protocol for a natural experiment evaluating the health benefits of ecological restoration of parks. *BMC Public Health, 20*(1), 638. doi:10.1186/s12889-020-08716-3

Peen, J., Schoevers, R. A., Beekman, A. T., & Dekker, J. (2010). The current status of urban-rural differences in psychiatric disorders. *Acta Psychiatrica Scandinavica, 121*(2), 84–93. doi:10.1111/j.1600-0447.2009.01438.x

Peterson, R. D., & Krivo, L. J. (2010). *Divergent social worlds: Neighborhood crime and the racial-spatial divide*. New York: Russell Sage Foundation.

Pozzi, F., & Small, C. (2001). *Exploratory analysis of suburban land cover and population density in the U.S.A.* Paper presented at the IEEE/ISPRS Joint Workshop on Remote Sensing and Data Fusion Over Urban Areas, Rome, Italy.

PRISM Climate Group. (2018). 30-year normals. [ASC file]. Retrieved from http://prism.oregonstate.edu/normals/

Ranson, M. (2014). Crime, weather, and climate change. *Journal of Environmental Economics and Management, 67*(3), 274–302. doi:10.1016/j.jeem.2013.11.008

Ratcliffe, J. (2010). Crime mapping: Spatial and temporal challenges. In A. R. Piquero & D. Weisburd (Eds.), *Handbook of Quantitative Criminology* (pp. 5–24). Berlin: Springer.

Rhew, I. C., Vander Stoep, A., Kearney, A., Smith, N. L., & Dunbar, M. D. (2011). Validation of the normalized difference vegetation index as a measure of neighborhood greenness. *Annals of Epidemiology, 21*(12), 946–952. doi:10.1016/j.annepidem.2011.09.001

Rhodes, T., Watts, L., Davies, S., Martin, A., Smith, J., Clark, D., . . . Lyons, M. (2007). Risk, shame and the public injector: A qualitative study of drug injecting in South Wales. *Social Science and Medicine, 65*(3), 572–585. doi:10.1016/j.socscimed.2007.03.033

Roe, J. J., Aspinall, P. A., Mavros, P., & Coyne, R. (2013). Engaging the brain: The impact of natural versus urban scenes using novel EEG methods in an experimental setting. *Environmental Science, 1*(2), 93–104. doi:10.12988/es.2013.3109

Roe, J. J., Thompson, C. W., Aspinall, P. A., Brewer, M. J., Duff, E. I., Miller, D., . . . Clow, A. (2013). Green space and stress: Evidence from cortisol measures in deprived urban communities. *International Journal of Environmental Research and Public Health, 10*(9), 4086–4103. doi:10.3390/ijerph10094086

Rosenfeld, R., & Fornango, R. (2007). The impact of economic conditions on robbery and property crime: The role of consumer sentiment. *Criminology, 45*(4), 735–768.

Rotton, J., & Cohn, E. G. (2001). Temperature, routine activities, and domestic violence: A reanalysis. *Violence and Victims, 16*(2), 203–215. doi:10.1891/0886-6708.16.2.203

Rotton, J., & Cohn, E. G. (2003). Global warming and U.S. crime rates: An application of routine activity theory. *Environment and Behavior, 35*(6), 802–825. doi:10.1177/0013916503255565

Royston, P., & White, I. R. (2011). Multiple imputation by chained equations (MICE): Implementation in Stata. *Journal of Statistical Software, 45*(4), 1–67. doi:10.18637/jss.v045.i04

Sadler, R. C., Pizarro, J., Turchan, B., Gasteyer, S. P., & McGarrell, E. F. (2017). Exploring the spatial-temporal relationships between a community greening program and neighborhood rates of crime. *Applied Geography, 83*, 13–26. doi:10.1016/j.apgeog.2017.03.017

Sampson, R. J., & Laub, J. H. (1993). Structural variations in juvenile court processing: Inequality, the underclass, and social control. *Law and Society Review, 27*(2), 285–311. doi:10.2307/3053938

Sarkisian, N., & Gerstel, N. (2015). Does singlehood isolate or integrate? Examining the link between marital status and ties to kin, friends, and neighbors. *Journal of Social and Personal Relationships, 33*(3), 361–384. doi:10.1177/0265407515597564

Schinasi, L. H., & Hamra, G. B. (2017). A time series analysis of associations between daily temperature and crime events in Philadelphia, Pennsylvania. *Journal of Urban Health, 94*(6), 892–900. doi:10.1007/s11524-017-0181-y

Schut, A. G., Ivits, E., Conijn, J. G., Ten Brink, B., & Fensholt, R. (2015). Trends in global vegetation activity and climatic drivers indicate a decoupled response to climate change. *PLoS One, 10*(10), e0138013. doi:10.1371/journal.pone.0138013

Scott, C. A., & Lutz-Ley, A. N. (2016). Enhancing water governance for climate resilience: Arizona, USA—Sonora, Mexico comparative assessment of the role of reservoirs in adaptive management for water security. In T. C. (Ed.), *Increasing resilience to climate variability and change: The roles of infrastructure and governance in the context of adaptation.* Berlin: Springer.

Setälä, H., Viippola, V., Rantalainen, A.-L., Pennanen, A., & Yli-Pelkonen, V. (2013). Does urban vegetation mitigate air pollution in northern conditions? *Environmental Pollution, 183*, 104–112. doi:10.1016/j.envpol.2012.11.010

Shaw, C., & McKay, C. (1942). *Juvenile deliquency and urban areas*. Chicago, IL: University of Chicago Press.

Shaw, M., van Dijk, J., & Rhomberg, W. (2003). Determining trends in global crime and justice: An overview of results from the United Nations surveys of crime trends and operations of criminal justice systems. In *Forum on Crime and Society* (Vol. 3, pp. 35–63). New York: United Nations Office on Drugs and Crime.

Skogan, W. G. (1990). *Disorder and decline*. New York: Free Press.

Snelgrove, A. G., Michael, J. H., Waliczek, T. M., & Zajicek, J. M. (2004). Urban greening and criminal behavior: A geographic information system perspective. *HortTechnology, 14*(1), 48–51. doi:10.21273/HORTTECH.14.1.0048

Staats, H., Jahncke, H., Herzog, T. R., & Hartig, T. (2016). Urban options for psychological restoration: Common strategies in everyday situations. *PLoS One, 11*(1), e0146213. doi:10.1371/journal.pone.0146213

Stansfield, R., & Parker, K. F. (2013). Teasing out the effects of macro-conditions on race-specific male homicide rates: Do distinct predictors vary by racial group and over time? *Social Science Research, 42*(3), 633–649. doi:10.1016/j.ssresearch.2012.12.015

Steffensmeier, D. J., Allan, E. A., Harer, M. D., & Streifel, C. (1989). Age and the distribution of crime. *American Journal of Sociology, 94*(4), 803–831.

Stevens, H. R., Beggs, P. J., Graham, P. L., & Chang, H. C. (2019). Hot and bothered? Associations between temperature and crime in Australia. *International Journal of Biometeorology, 63*(6), 747–762. doi:10.1007/s00484-019-01689-y

Szantoi, Z., Escobedo, F., Wagner, J., Rodriguez, J. M., & Smith, S. (2012). Socioeconomic factors and urban tree cover policies in a subtropical urban forest. *GIScience & Remote Sensing, 49*(3), 428–449. doi:10.2747/1548-1603.49.3.428

Tam, M. Y. S., & Bassett, G. W. (2004). Does diversity matter? Measuring the impact of high school diversity on freshman GPA. *Policy Studies Journal, 32*(1), 129–143. doi:10.1111/j.0190-292X.2004.00056.x

Taylor, R. B., Groff, E. R., Elesh, D., & Johnson, L. (2014). *Intra-metropolitan crime patterns predictors, and predictions, executive summary*. Retrieved from

Thaler, R. (1978). A note on the value of crime control: Evidence from the property market. *Journal of Urban Economics, 5*(1), 137–145. doi:10.1016/0094-1190(78)90042-6

Tong, R. Z., Song, H., Sun, W. C., Xu, Z. X., Yao, X. L., & Yu, J. S. (2019). Analyzing the impact of climate change on natural vegetation greenness using improved statistical vegetation index simulation model. *Applied Ecology and Environmental Research, 17*(2), 4677–4691. doi:10.15666/aeer/1702_46774691

Troy, A., Grove, J. M., & O'Neil-Dunne, J. (2012). The relationship between tree canopy and crime rates across an urban–rural gradient in the greater Baltimore region. *Landscape and Urban Planning, 106*(3), 262–270. doi:10.1016/j.landurbplan.2012.03.010

Tyrväinen, L., Ojala, A., Korpela, K., Lanki, T., Tsunetsugu, Y., & Kagawa, T. (2014). The influence of urban green environments on stress relief measures: A field experiment. *Journal of Environmental Psychology, 38*, 1–9. doi:10.1016/j.jenvp.2013.12.005

U.S. Census Bureau. (2015). *2015 TIGER/Line Shapefiles (machine readable data files)*.

U.S. Census Bureau. (2016). *Measuring America: Our changing landscape*. Retrieved from https://www.census.gov/content/dam/Census/library/visualizations/2016/comm/acs-rural-urban.pdf

U.S. Census Bureau. (2018). Census regions and divisions of the United States. Retrieved from https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf

van Dijk, J., Tseloni, A., & Farrell, G. (Eds.). (2012). *The international crime drop: New directions in research*. Basingstoke, UK: Palgrave Macmillan.

Walsh, A. (2011). Measuring crime and criminal behavior. In A. Walsh (Ed.), *Criminology: The Essentials* (pp. 21–40). Los Angeles, CA: SAGE Publications.

Walsh, A., & Jorgensen, C. (2017). *Criminology: The essentials* (3rd ed.). New York: SAGE Publications Inc.

Wandersman, A., & Nation, M. (1998). Urban neighborhoods and mental health: Psychological contributions to understanding toxicity, resilience, and interventions. *American Psychologist, 53*(6), 647–656. doi:10.1037/0003-066X.53.6.647

Webb, N. P., Marshall, N. A., Stringer, L. C., Reed, M. S., Chappell, A., & Herrick, J. E. (2017). Land degradation and climate change: Building climate resilience in agriculture. *Frontiers in Ecology and the Environment, 15*(8), 450–459. doi:10.1002/fee.1530

White, I. R., Royston, P., & Wood, A. M. (2011). Multiple imputation using chained equations: Issues and guidance for practice. *Statistics in Medicine, 30*(4), 377–399. doi:10.1002/sim.4067

White, M. P., Alcock, I., Grellier, J., Wheeler, B. W., Hartig, T., Warber, S. L., . . . Fleming, L. E. (2019). Spending at least 120 minutes a week in nature is associated with good health and wellbeing. *Scientific Reports, 9*(1), 7730. doi:10.1038/s41598-019-44097-3

Wicherts, J. M., Wu, C.-D., McNeely, E., Cedeño-Laurent, J. G., Pan, W.-C., Adamkiewicz, G., . . . Spengler, J. D. (2014). Linking student performance in Massachusetts elementary schools with the "greenness" of school surroundings using remote sensing. *PLoS One, 9*(10), e108548. doi:10.1371/journal.pone.0108548

Wilkowski, B. M., & Robinson, M. D. (2008). Guarding against hostile thoughts: Trait anger and the recruitment of cognitive control. *Emotion, 8*(4), 578–583. doi:10.1037/1528-3542.8.4.578

Wilkowski, B. M., Robinson, M. D., & Troop-Gordon, W. (2010). How does cognitive control reduce anger and aggression? The role of conflict monitoring and forgiveness processes. *Journal of Personality and Social Psychology, 98*(5), 830–840. doi:10.1037/a0018962

Wolfe, M. K., & Mennis, J. (2012). Does vegetation encourage or suppress urban crime? Evidence from Philadelphia, PA. *Landscape and Urban Planning, 108*(2-4), 112–122. doi:10.1016/j.landurbplan.2012.08.006

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

World Health Organization. (2011). *Burden of disease from environmental noise: Quantification of healthy life years lost in Europe*. Copenhagen, Denmark: WHO.

Wu, X., & Lum, C. (2019). The practice of proactive traffic stops. *Policing: An International Journal, 43*(2), 229–246. doi:10.1108/pijpsm-06-2019-0089

Zhou, W., Troy, A., Morgan Grove, J., & Jenkins, J. C. (2009). Can money buy green? Demographic and socioeconomic predictors of lawn-care expenditures and lawn greenness in urban residential areas. *Society & Natural Resources, 22*(8), 744–760. doi:10.1080/08941920802074330

Zillmann, D. (1983). Transfer of excitation in emotional behavior. In J. T. Cacioppo & R. E. Petty (Eds.), *Social Psychophysiology* (pp. 215–240). New York: Guilford Press.

Table 1. Descriptive statistics for demographic and environmental characteristics of 290 cities over 30 years, final year in each 5-year period shown as column header.

	Year					
Time-Varying Covariates	**1990**	**1995**	**2000**	**2005**	**2010**	**2015**
Homicide rate per 100,000 population, mean (sd)	**52.1** (50.6)	60.8 (60.8)	42.7 (43.1)	42.1 (43.2)	39.6 (41.3)	33.5 (36.7)
Greenness (NDVI), mean (sd)	0.41 (0.14)	0.44 (0.12)	0.42 (0.12)	0.43 (0.11)	0.42 (0.12)	0.43 (0.12)
Population density in 1000s/mi^2, mean (sd)	3.1 (2.7)	3.3 (2.8)	3.4 (2.8)	3.5 (2.7)	3.7 (2.7)	3.9 (2.8)
Percent male aged 15-24y, mean (sd)	16.2 (4.1)	15.9 (4.1)	15.7 (4.2)	14.7 (3.2)	16.1 (4.5)	15.4 (4.3)
Percent ≥ 25y with no diploma, mean (sd)	22.8 (9.5)	21.4 (9.1)	19.9 (9.2)	16.8 (8.3)	15.8 (7.8)	14.4 (7.6)
Percent ≥ 16y who are unemployed, mean (sd)	4.4 (1.3)	4.3 (1.3)	4.2 (1.4)	7.7 (2.7)[b]	7.8 (2.2)	4.5 (1.6)
Percent below poverty line, mean (sd)	14.6 (7.1)	14.6 (6.6)	14.5 (6.5)	15.8 (7.0)	18.5 (7.3)	17.6 (7.1)
Percent single mother households, mean (sd)	19.6 (7.3)	35.1 (7.5)	50.5 (9.7)	**52.2 (15.6)**	**46.2 (18.2)**	**22.6 (9.2)**
Ethnic diversity index[a], mean (sd)	0.42 (0.2)	0.47 (0.2)	0.51 (0.1)	0.53 (0.1)[c]	0.56 (0.1)[d]	0.57 (0.1)[e]
Annual temperature in °F, mean (sd)	60.1 (8.1)	59.8 (8.2)	60.1 (8.0)	60.7 (8.5)	60.2 (7.8)	59.7 (7.9)

Values for each year are reported as mean (standard deviation) and represent the mean of the preceding 5-year period.

[a]Values closer to one indicate higher heterogeneity.

Cities with missing data n (%):

[b]25 (8.62%), [c]5 (1.72%), [d]5(1.72%), [e]6 (2.07%).

Table 2. Results of the multilevel conditional linear growth curve modelling.

Fixed effects	β	95% CI	SE	df	*t*-value	VIF
Intercept	**25.25**	**– 11.74, 62.51**	**18.76**	**334**	**1.346**	0.00
Average greenness (NDVI), re-scaled by 100	**– 0.30**	**– 0.55 –0.05**	**0.13**	**1411**	**– 2.397***	1.11
Population density in 1000s/mi^2	**– 0.0002**	**– 0.0018, 0.0013**	**0.0008**	**546**	**– 0.290**	1.23
Percent male aged 15-24y	**– 0.25**	**– 0.80, 0.30**	**0.28**	**1655**	**– 0.913**	1.07
Percent ≥ 25y with no diploma	**0.84**	**0.53, 1.15**	**0.15**	**1556**	**5.458*****	1.37
Percent ≥ 16y who are unemployed	**0.65**	**– 0.08, 1.37**	**0.37**	**1444**	**1.762**	1.15
Percent below poverty line	**1.04**	**0.65, 1.44**	**0.19**	**1706**	**5.358*****	1.41
Percent single mother households	**0.08**	**– 0.01, 0.16**	**0.04**	**1402**	**1.814**	1.03
Ethnic diversity index[a]	**55.65**	**40.56, 740.72**	**7.65**	**1711**	**7.274*****	1.10
Mean annual temperature in °F	**– 0.44**	**– 0.94, 0.06**	**0.25**	**530**	**– 1.743**	1.05
Random effects	**var**	**sd**	**ICC**			
City	**1097.7**	**33.13**	**0.81**			
Region	**180.1**	**13.42**	**0.41**			
Year	**130.7**	**11.43**	**0.33**			
Residual	**263.2**	**16.22**				
Akaike information criterion (AIC)	**15424.9**					

SE = standard error; var = variance; sd = standard deviation; ICC = Intraclass correlation coefficient.

[a]*Adjusted for inflation to 2015 USD.*

[b]*Values closer to one indicate higher heterogeneity.*

*Significance at p-value: ***<0.001, **<0.005, *<0.05.*

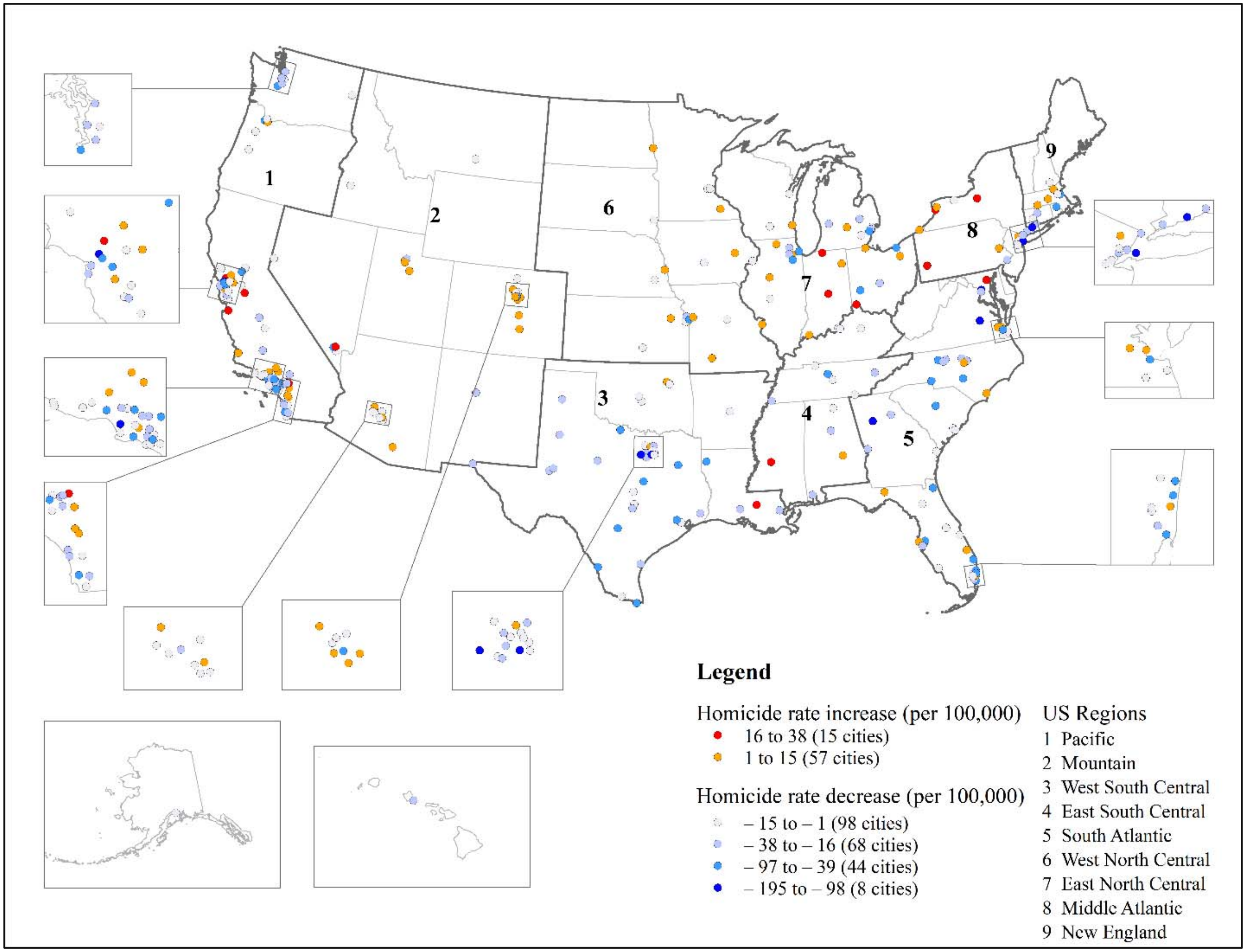

Figure 1. Homicide rate differences between the last five-year period (2011–2015) and the first five-year period (1986–1990) across 290 US cities.

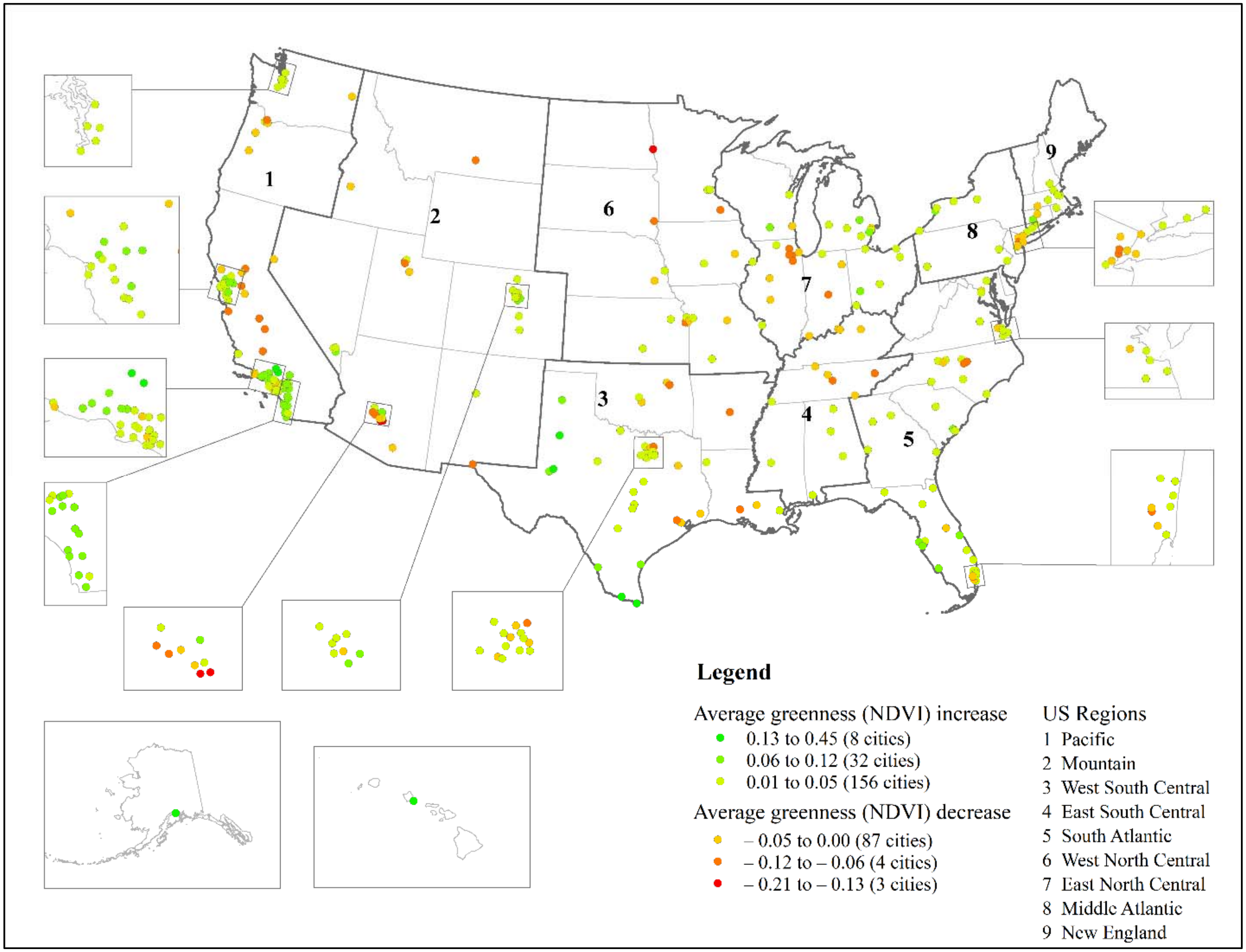

Figure 2. Average greenness changes between the last five-year period (2011–2015) and the first five-year period (1986–1990) across 290 US cities.