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Associations between tree characteristics and street crime: A case study in downtown Austin, TX

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ABSTRACT

Urban trees play a critical role in livable and safe communities. Few studies have attempted to comprehensively examine a set of tree-related characteristics by using multiple measures through aerial imagery, street view imagery, and tree inventories in relation to street crime, especially in downtowns with busy street activities. This study examined to what extent tree attributes were associated with street crime at the street segment scale. This study also aimed to investigate the relationships of proxy measures for view-obstructive levels of trees with street crimes. Using downtown Austin, Texas as a study area, we analyzed micro-level crime incidents at a street segment level: 518 street segments in total within the downtown neighborhood. We used violent and property crime incidents that occurred on the streets between 2014 and 2019. A series of negative binomial regressions were employed to explore the associations of the characteristics of trees with street crime. After adjusting for socioeconomic and built environment variables, tree canopy coverage using aerial imageries and tree coverage using Google Street View images had inverse relationships with both violent and property street crime rates while size-weighted tree density using tree inventory was only associated with violent street crime rate. The tree coverage in the bottom-half of GSV images was inversely associated with violent street crime rate but not with property street crime rate. Additionally, we found that large-sized tree density (DBH≥30 cm and 40 cm) was inversely associated with both types of crime rates while small-sized tree density (DBH≤20 cm) was positively associated with property crime rate. While further research is needed to validate the view-obstructing effects of small-sized tree density and tree coverage in the bottom-half of GSV images, it is important to consider factors such as appropriate tree size and the potential for view-obstruction to maximize the benefits of urban trees in crime prevention.

1. Introduction

With the high movement of goods and people, downtown areas play a vital role in local economic and cultural activities (The City of Calgary, 2021). They offer a variety of attractions and gathering places for visitors and residents, as well as employment opportunities, particularly for those who commute via public transportation (Amore, 2019). Due to the enormous volume of various activities, non-residential central business districts are particularly susceptible to urban crime. Rising violent and property crimes can lead to safety concerns, which could impede the development of downtown areas. Most municipal governments in the U. S. have made an effort to devote more funds to improving the image of downtown areas, promoting safety, and reducing downtown crime (Bowes, 2007). It is crucial to understand how the street environment influences downtown crime because daily activities of tourists, employees, and even residents take place on streets in downtown areas.

Streets with a high volume of everyday activity may disproportionately attract more criminals and targets, which might increase crime (Felson & Boivin, 2015). Previous studies have identified various micro-scale street environmental determinants of crime, suggesting a significant spatial clustering of crime incidents in relation to street environmental features of urban areas (Groff et al., 2010). For example, buildings with good visibility, having more balconies, windows, or shop windows facing the streets, can help reduce crime (Hendricks et al.,

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1999). The “eyes on the street” theory proposed by Jacobs (1961) highlighted the importance of surveillance for public safety through monitoring the street activities by residents and shopkeepers. Urban design strategies may also encourage visitors to walk to destinations more comfortably and safely by reducing crime concerns or reducing actual crime incidents. In particular, installing and fixing streetlights has been one of the best ways to improve public safety and make crime less likely to happen (Lawson et al., 2018). Yard landscaping, which includes yard trees, garden hoses, and lawns, was also linked to less crime. This is because more attractive landscaping acts as a "cue to care" and brings more "eyes on the street" (Troy et al., 2016) to deter criminal activity.

1.1. Mechanism of the effect of urban trees on crime

Urban trees are considered as an amenity that brings several health and social benefits, including promoting people’s physical and mental health, attracting more tourists, and even improving safety by reducing crime (Wolf et al., 2020). Specifically, individuals exposed to greater tree canopy experienced less psychological distress (Astell-Burt & Feng, 2019). Collaborative non-profit programs for planting trees can also have a positive social impact by strengthening social bonds, shared social trust, and social cohesion in the neighborhoods (Watkins et al., 2018). Additionally, the presence of shade trees may attract visitors to downtown or shopping district (Wolf, 2004). Finally, tree canopy was found to be inversely associated with violent and property street crime rates (Lee, 2021).

Urban trees can reduce crimes by mitigating mental fatigue through the restorative effect and reduction of psychological stressors. Urban streets can add visual aesthetics to the streetscapes, inviting more street activities and increasing surveillance through more eyes on the street (Kuo & Sullivan, 2001). When walking on the streets, pedestrians may face unexpected situations, such as pedestrian falls, traffic injuries, and criminal activity (Elvik & Bjørnskau, 2019). Urban trees can help reduce psychological stress in these situations and can have a favorable impact on human health (Mennis et al., 2018). According to Kaplan & Kaplan (1989), vegetation has a therapeutic effect on urban dwellers who have been subjected to excessive stress and cognitive fatigue. Greater social cohesion and perceived stress alleviation have been associated with streets with more trees and tree canopy (de Vries et al., 2013; Ulmer et al., 2016). Street trees may help counteract unhealthy environmental factors like traffic pollution and noise from busy roads that can be detrimental to mental health (Dadvand et al., 2014). Additionally, aesthetically pleasing trees can provide resting and inviting locations and increase the likelihood that people would engage in outdoor activities there (Tabatabaie et al., 2019). Increased outside activity and social contact may make it more difficult for criminals to engage in criminal activity, according to Jacob’s "eyes on the streets." However, crowds and high-activity streets, such as bus stops (Levine et al., 1986; Lee et al., 2023) and busy business and commercial properties (Tillyer & Walter, 2019), may also become high crime spots.

The effects of trees on crime can also differ depending on the size of the tree. A study in Portland conducted by Donovan & Prestemon (2012) measured the size and number of trees in the public right-of-way and found that smaller trees on private lots were associated with increased crime while taller trees on private lots were associated with decreased crime. This is mainly because lower and overgrown trees may obscure views and even provide cover for criminals to hide (Donovan & Prestemon, 2012). Troy et al. (2012) found that an increase in tree canopy was associated with a decrease in crime in the city and the surrounding county of Baltimore, Maryland. A study in Bogota, Colombia found that public treescapes with taller trees and higher tree density were inversely associated with homicides (Escobedo et al., 2018). A recent study in New York City also found that small-sized tree density was positively associated with crime rates while large-sized tree density was negatively associated with crime rates (Lin et al., 2021).

1.2. Measurements of trees and crime

Several studies attempted to quantify trees to explore the influence mechanism of trees on crime, but quantifying trees is challenging due to the lack of universal methods to measure trees. The most frequently used method for measuring tree canopy is overhead view imageries from aircrafts, drones, or satellites to extract tree canopy cover. This method allows researchers to quantify tree canopy coverage over large geographic areas from an overhead view perspective. Troy et al. (2012) used land cover data to measure tree canopy cover and found a strong inverse relationship between tree canopy and an index of crime in Baltimore, US (Troy et al., 2012). Landry & Chakraborty (2009) used satellite imageries to examine the relationships among social inequities and public right-of-way trees. However, tree canopy using aerial imageries is often limited in providing detailed information, such as tree size, crown shape, and canopy height (Jiang et al., 2017).

Another measurement to identify trees is the street view imagery. Street view imageries are commonly taken from cameras mounted on the roof of automobiles and provide eye level perspective, which can allow researchers to evaluate the degree to which tree canopy may block the sightline for surveillance. Recent literature used computer vision technology to extract the amount of trees as they appear on street view imageries. For example, Zhou et al. (2021) utilized street view imagery to measure micro built environment characteristics to understand drug activities and street robberies. Street view imagery captures both public and private trees, but some trees behind objects or other trees cannot be detected from the road Table 1.

Tree inventory is the last method of measuring trees in our study. Given the supportive methodological and technological development (e.g., i-Tree (2006)), many US city authorities have adopted tree inventory (Nielsen et al., 2014). Because tree inventory involves manual, on-site data collection, it arguably offers the most accurate information of tree canopy. It can also provide rich information about individual tree characteristics, including exact location, diameter at breast height, and species. Escobedo et al. (2018) used tree inventory, including structural characteristics of trees (e.g., crown cover, densities, heights) and found that taller trees (i.e., more than 16 in. of the diameter at breast height) and higher tree density were associated with fewer homicides in Bogota, Columbia. Although trees on private property may also have an impact on crime, tree inventories typically only include public trees. Furthermore, due to its manual nature, producing new tree inventory data might be resource intensive.

1.3. Key research aims

Although considerable efforts have been made towards addressing the role of the overall tree canopy on crime, few studies have attempted to comprehensively examine a set of tree-related characteristics by using multiple measures from aerial imageries, street view imageries, and audit-based inventory in relation to street crime, especially in the city’s downtown with busy street activities. Additionally, the effects of urban vegetation on crime at the street segment level have not been explored. This study sought to examine to what extent the characteristics of trees were associated with street crime at the street segment scale using tree measurements from three different data sources. Furthermore, by dividing street view imageries and tree inventory, we also identified the view-obstructive aspects of trees. Then, we tested how and to what extent tree sizes and view-obstructive levels are associated with different types of street crimes. Understanding the influencing mechanism of urban trees on crime is important to crime prevention and urban forestry management.

Table 1
Descriptive Statistics of Street Crime, Tree Measurements, and Socio-Demographic Variables.

	Mean (SD)	Min~Max	Data Source
Dependent variables			
Violent street crime	1.808 (8.225)	0.000–115.750	APD 2014–2019
Property street crime	2.169 (5.544)	0.000–61.500	APD 2014–2019
Independent variables			
tree-aerial (tree canopy coverage)	0.112 (0.115)	0.000–0.662	Austin Open Data, 2014
tree-GSV (tree image coverage)	0.098 (0.068)	0.000–0.376	Google Maps API
tree-GSV (tree image coverage in bottom half)	0.017 (0.019)	0.000–0.205	
tree-inventory (size-weighted tree density, total DBH cm/ street length in m)	2.895 (2.683)	0.000–16.434	Austin Open Data, 2020
tree-inventory (tree density with DBH < 10 cm)	0.029 (0.033)	0.000–0.201	
tree-inventory (tree density with DBH < 20 cm)	0.056 (0.053)	0.000–0.339	
tree-inventory (tree density with DBH >30 cm)	0.040 (0.044)	0.000–0.252	
tree-inventory (tree density with DBH >40 cm)	0.026 (0.034)	0.000–0.181	
Socio-demographic variables			
Employment density	1.381 (2.794)	0.000–26.077	LEHD LODES 2014
Population density	0.001 (0.002)	0.000–0.013	ACS 2014–2018
Black population density	0.006 (0.027)	0.000–0.334	ACS 2014–2018
Median household income ($1000)	93.405 (28.044)	20.868–148.411	ACS 2014–2018
(Lag) employment density	1.379 (1.009)	0.085–4.586	ACS 2014–2018
(Lag) population density	0.001 (0.001)	0.000–0.006	ACS 2014–2018
(Lag) Median household income ($1000)	93.804 (25.163)	30.344–148.411	ACS 2014–2018
(Lag) Black population density	0.006 (0.007)	0.000–0.039	ACS 2014–2018
Built environmental variables			
Walk Score	90.946 (7.463)	56–99	Walk Score, 2021
Bus stop density	0.001 (0.001)	0.000–0.006	Austin Open Data
Exposure variable			
Street length (m)	115.096 (34.462)	15.07–337.52	Austin Open Data
Binary variables			
Presence of residential use	Presence: 202 (39.0%)		Austin Open Data
Presence of commercial use	Presence: 213 (41.1%)		
Presence of parks	Presence: 71 (13.7%)		
Presence of surface parking	Presence: 82 (15.8%)		

2. Material and methods

2.1. Study area

Austin, Texas has experienced rapid population growth in recent years, with the population of the Austin metro area increasing from 1.7 million to 2.3 million between 2010 and 2020. The majority of the population growth is largely due to the influx of domestic and international migration (Ramser, 2022). However, this influx of people may also contribute to an increase in crime rates, as is often the case in growing cities (Stansfield et al., 2013). Yang et al. (2019) reported that certain types of crime, such as automobile theft and robbery, tend to outpace the population. Despite the growth and potential risks, Austin is still known for its natural beauty, boasting an estimated 33.8 million trees that cover 30.8% of the overall area (Nowak et al., 2016). In fact, the city has set a goal to increase tree canopy coverage to 50% by 2050 as part of its Climate Equity Plan (City of Austin, 2021).

This study mainly focuses on Downtown Austin, a place for living, working, and playing with diverse land uses. The area is 1000 acres (4.04 km2), defined by Martin Luther King Jr (MLK) Boulevard, IH 35, Lady Bird Lake, and Lamar Boulevard (see Fig. 1). The simple grid form of downtown blocks, designed by Edwin Waller in 1839, provides easy connections between urban elements, including districts, parks, and facilities (Austin City Council, 2011). Downtown Austin is home to 16,700 residents and is a major employment hub for 99,000 employees in 2020 (Downtown Austin Alliance, 2021). Cultural and commercial amenities (e.g. museums, retails, restaurants, etc.) of Downtown attract visitors to Austin City, more than 30 million visitors annually (Visit Austin, 2022).

To analyze micro-level crime incidents, we used a street segment as the unit of analysis. Street segments, also known as street block faces, are a more frequently used analytical unit in the fields of place and criminology. According to Weisburd et al. (2004), a street segment is described as “the two block faces on both sides of a street between two intersections”. There are 518 street segments within the downtown neighborhood.

2.2. Measures

2.2.1. Street crime

The dependent variable in this study is the count of crime that occurred on the streets. We used crime data reported by the Austin Police Department (APD). The APD computerized records of each call-for-service with their detailed dispatch information, including the category of the incident, occurred/report date & time, location type, and X-Y coordinates. For this research, we used crime events that occurred only on the streets, reported from 2014 to 2019. In alignment with previous studies (Lee & Contreras, 2021; Willits et al., 2013), we used six-year crime data to mitigate the effects of measurement errors, infrequent occurrences of street crime, and year-to-year variation in criminal incidents. This data was collected through the City of Austin data portal (City of Austin, 2022). Crime types in this study included violent crime (i.e., assault, aggravated assault, robbery) and property crime (i.e., burglary, motor vehicle theft, theft) that occurred on the streets as dependent variables. There was a total of 942 incidents of street violent crime and 1177 incidents of street property crime.

2.2.2. The characteristics of trees

Three data sources were used to measure the presence and characteristics of trees, including aerial imageries, street view imageries, and tree inventory. First, the characteristics of trees in an overhead view were derived using the combination of aerial imagery and remote sensing technology (heretofore, tree-aerial). Specifically, the U.S. Department of Agriculture’s National Agriculture Imagery Program (NAIP) provided aerial images taken during the "leaf-on" agricultural growing season of Austin, TX in 2014. Each pixel of the 2014 high-resolution aerial images (1 ×1 m pixels) was classified into one of the tree canopy (including tree leaves, branches, and stems) and non-tree canopy classes. The data is available for download on the official City of Austin Open data portal (data.austintexas.gov). While the accuracy assessment report was not available in 2014, a report by the City of Austin’s Watershed Protection Department stated that the classifier for detecting tree pixels in the NAIP aerial images had high degree of accuracy, indicating that 93% of pixels classified as tree canopy in the GIS feature class were accurate representations of actual tree canopy (Halter, 2014). Street trees were extracted by the public right-of-way intersecting with the classified aerial imageries. The proportion of land area covered by tree canopy was calculated by dividing the number

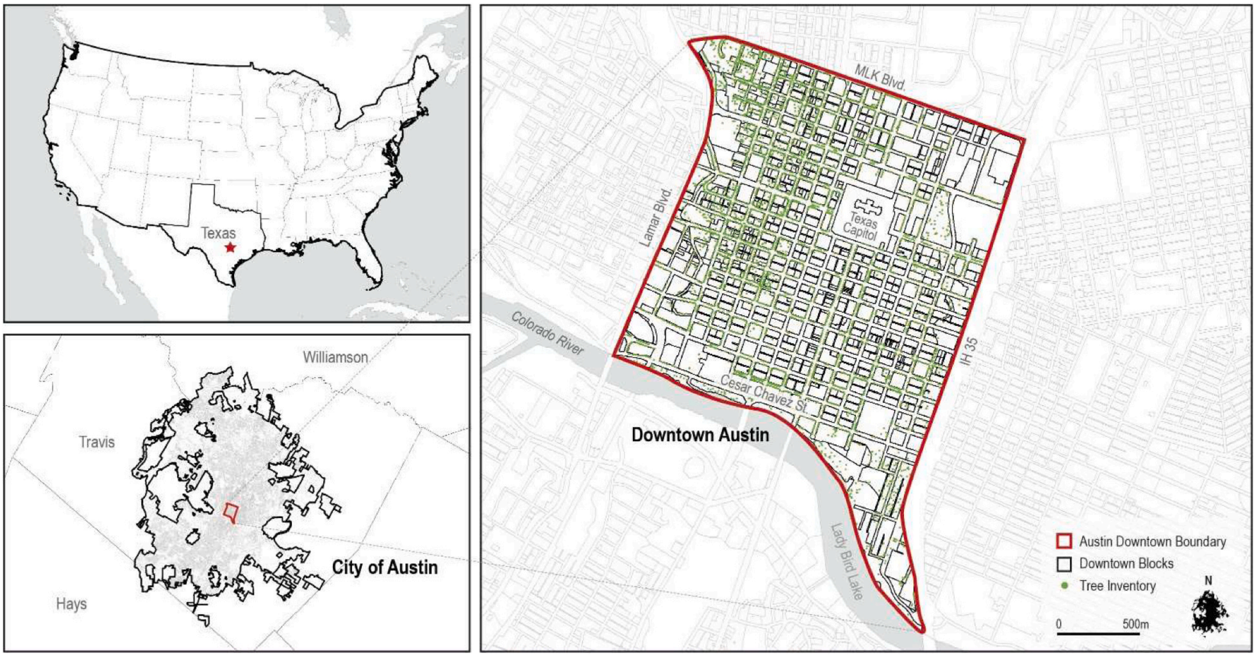


Fig. 1. Location of Downtown Austin.

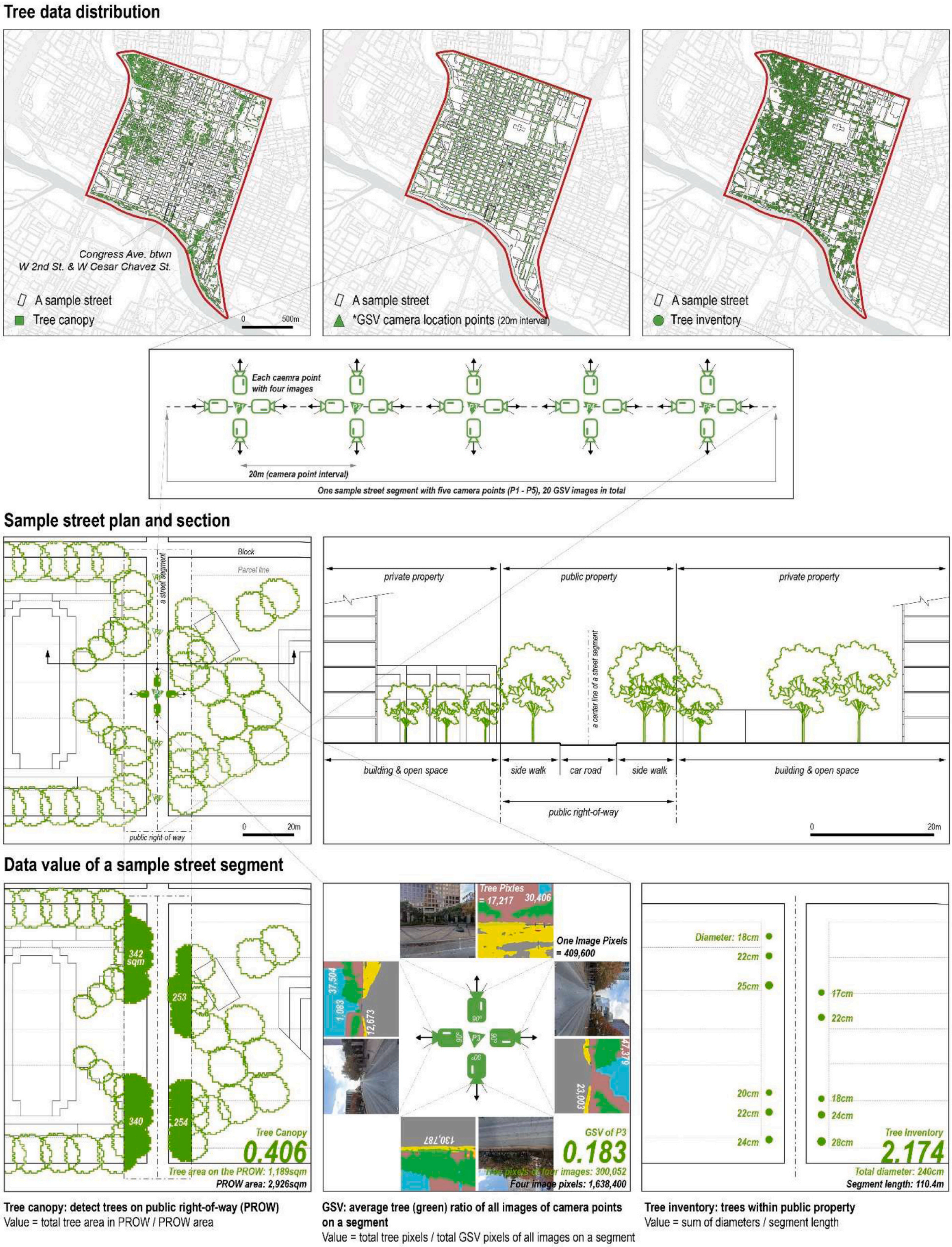
of pixels representing tree canopy by the total number of pixels within the public right-of-way areas. As exemplified in Fig. 2, the value of tree canopy coverage at a sample street segment is 0.406 (i.e., 1,189 sqm of tree canopy areas divided by 2,926 sqm of the public right-of-way areas).

Second, the Google Street View (GSV) images were used to measure the amount of greenery at eye level (tree-GSV) as illustrated in Fig. 2. The GSV images were downloaded for all street segments in the study area at every 20 m using the GSV application programming interface (API). The size of images downloaded through the GSV API was 640 by 640 pixels. At each image location (i.e., the location at which GSV images were downloaded), four images were downloaded with the field of view equal to 90 to cover a full 360° view (see Fig. 2). This study downloaded a total of 11,052 street view images. The average year the images were taken is 2020.3, with the standard deviation of 1.194. Tree image coverage was extracted from these images using a computer vision model called Pyramid Scene Parsing Network (PSPNet), which has a pixel-wise accuracy of 80.04%. PSPNet labels each pixel in a given image with one of 150 categories, including tree, grass, plant, and sidewalk (Koo et al., 2022; Xie et al., 2022; Zhao et al., 2017; Zhou et al., 2021). For each image location, the total number of pixels for each category was divided by 1,638,400 (i.e., 640 (height) x 640 (width) x 4 (number of images at one image location) to convert the raw pixel count into proportions. We calculated the tree image coverage with the proportion of trees by the proportion of all images within each street segment. The calculated tree image coverage represents the average proportions of trees as seen from eye level for each street segment. For example, the tree image coverage in the GSV images for a specific street segment shown as P3 in Fig. 2 is 0.183. This is calculated by dividing the total number of pixels that represent trees in the four images at that location (300,052 pixels) by the number of all pixels in the four images (640 pixels times 640 pixels times 4 image = 1,638,400 pixels). As there can be multiple locations at which GSV imageries were downloaded along a given street segment, we took the average of the proportion of tree pixels across all locations along that street segment.

Third, the street tree inventory dataset (tree-inventory) of 2020 was provided from the Austin Open Data, which includes the number of trees, diameter at breast height, and species. The tree-inventory data is developed using multiple sources, including the Development Services Department's Tree Division, Parks and Recreation Department, and the Public Works Department's downtown tree inventory. Previous studies have identified that the tree height and diameter at breast height (DBH) have strong and positive relationships though they vary depending on tree types, growth rate, or other geo-climate conditions (Avsar, 2004; Mugasha et al., 2013; Pepper et al., 2001). Thus, we assumed that DBH is a factor representing tree size and height. To aggregate the information of individual trees up to street segment level, we calculated size-weighted tree density by dividing the sum of DBH of trees on a given street segment by the length of the street segment (total DBH cm of trees/ street length measured in meters). For example, the value of size-weighted tree density at the sample street segment shows 2.174 (Fig. 2) Because this measure can reflect both density and size of trees, it can better explain the volume of trees and may be conceptually comparable to other tree measures (e.g., tree canopy coverage or tree image coverage) derived from aerial and street view images.

One of the key research aims of this study is to examine how trees with the potential of being view-obstructive are associated with crimes. The literature suggests that trees that are larger and/or taller may provide the benefits of greenery while reducing the possibility of being view-obstructing (Donovan & Prestemon, 2012). This study used different approaches to derive information about the potential of being view-obstructive depending on data sources for tree measurements. The tree-inventory data does not contain information about tree height, canopy width, or the shape of tree canopy. Instead, this study used the DBH as a proxy of their size. Multiple DBH thresholds were tested, including 10 cm, 20 cm, 30 cm, and 40 cm, to find the optimized DBH that is most closely associated with street crimes. We then calculated the density of larger trees (i.e., the number of large trees divided by the length of street segment) that have the DBH measure equal to or greater than 30 cm or 40 cm. We also defined the density of smaller trees using the number of trees that are equal to or smaller than 10 cm or 20 cm. This method is consistent with previous studies (Lin et al., 2021; Troy et al., 2016).

The counterpart measure for view-obstructive levels of trees was calculated using tree image coverage in the bottom-half of GSV images. GSV images are typically captured from a camera mounted on the roof of a vehicle, approximately 2 ~ 2.5 m above the ground, with flat horizontal view. In this study, the bottom half of GSV images captured trees



*GSV camera location points are located on every 20m of street segments (e.g. five camera points on a 100m - 119m street segment). Each camera point creates four 90 degree pictures, covering a 360 degree veiw. This sample street with 110m in length has five camera location points with 20 images in total. The GSV value of this street segment will be the average tree pixel ratio of the 20 images.

Fig. 2. Three types of tree data.

that represent the part of the trees that is below eye level (see Fig. 3 for a detailed graphic representation). The number of pixels representing trees in the bottom half of each GSV image was calculated, and we converted this into proportions by dividing it by the total pixel number. The multiple tree images covered in bottom-half were then averaged for each street segment.

2.2.3. Control variables

We included relevant sociodemographic and built environment characteristics that have been shown to be associated with crime in order to lessen the influence of other extraneous factors on criminal activity. As for sociodemographic variables, we included black population density, population density, and employment density. Because street segments are in the middle of two different blocks, we calculated the average values of these two blocks in order to distribute the block data to the street segment (Kim, 2018). We utilized 5-year estimates from the American Community Survey (ACS) for 2014–2018 to calculate black population density and the total population density. Employment density at census block level and median household income at census block group level were employed from the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) and the ACS. In addition, we produced a spatial-weights matrix with row standardization based on distance. The definition of "neighbors" was established such that all street segments, exhibiting inverse-distance decay, situated within a 400-meter (quarter mile) range of the midpoint of a street segment were included.

Several built environment-related variables were also included in the models based on previous literature. For example, we measured whether or not adjacent blocks to each street segment (i.e., within 100 ft) contained residential land use, commercial land use, or park or open space land use. Using ArcGIS 10.7, we created a 30 m (i.e., 100 ft) buffer from each street segment, intersected with adjacent land uses, and then calculated the proportion and areas of different land uses at the street segment level. Since bus stations and parking facilities are often the sites of crime (Liggett et al., 2001), we included the density of bus stops or parking lots adjacent to the street segment. The percentage of sidewalks using GSV was also included in the final model, as sidewalks are common settings where people walk and face criminal activity (Hipp et al., 2021). Likewise, we also included a Walk Score based on the middle point of each selected street segment. Walk Score has been used as an indicator of local walkability, which showed a significant association with street crime in the previous studies (Lee, 2021).

2.3. Analytical approach

Negative binomial models were used to explain the associations of tree characteristics with street crime because street crime incidents across the street segment were not normally distributed, which showed overdispersion. Similar to other studies (Kim & Hipp, 2021; Osgood, 2000), we also added street length as an exposure variable, which can make the outcome interpretable as a logged street crime rate (i.e., number of street crime incidents from 2014 to 2019 per length of street segment). We also included spatial lagged sociodemographic variables in order to control for the spatial autocorrelation of the model, which is consistent with earlier studies (Lee & Contreras, 2021). The general form of these model is expressed as follows:

$$\log(E(y)) = \alpha + \beta_1 G_i + \beta_2 D + \beta_3 WD + \beta_4 B + \log(l),$$

where y is the number of crimes on street segment, G_i is different characteristics of trees (tree-aerial, tree-GSV, and tree-inventory), D is a matrix of the sociodemographic characteristics, WD is a matrix of the spatially lagged sociodemographic characteristics, B is a matrix of built environmental characteristics, and l is the exposure variable (the length of the street segment).

This study presents a total of four groups of regression models. The first group of regression models (M1–1 ~ M1–3 for violent crime in Tables 2 and M2–1 ~ M2–3 for property crime in Table 3) regressed the number of violent and property crimes on tree-aerial, tree-GSV, and tree-inventory, respectively while adjusting for employment density, population density, black population density, median household income of the adjacent block groups, and their spatially lagged variants. The second group of models (M1–4 ~ M1–6 for violent crime in Tables 2 and M2–4 ~ M2–6 for property crime in Table 3) added a set of built environment variables as additional control variables, including Walk Score, bus stop density, the presence of surface parking lots, and the presence of residential, commercial, and park land uses in the adjacent parcels, respectively. The third group of models tested the average tree coverage in bottom-half of GSV images (M3–1 for violent crime and M3–2 for property crime in Table 4). Finally, the fourth group of models added the density of trees whose DBH is 10 cm, 20 cm, 30 cm, and 40 cm (M4–1 ~ M4–4 for violent crime and M4–5 ~ M4–8 for property crime in Table 4). Tree-aerial doesn't allow size or height consideration and was not considered in this group.

We assessed the Moran's I values of the residuals from the negative binomial regression models that incorporated spatially lagged socioeconomic variables. Our aim was to determine if there was any additional spatial autocorrelation present in the residuals. We found no evidence to suggest the presence of such autocorrelation. In fact, the Moran's I values of the residuals in all models were consistently very small, always less than 0.045, indicating a negligible level of correlation.

3. Results

3.1. Summary statistics

Table 1 shows the descriptive statistics for all variables used in the analysis. The average number of violent street crime incidents and property street crime incidents were 1.8 and 2.2 respectively at the street segment levels (n = 518). The average tree canopy percentage by street canyon using aerial images in downtown areas was 11.2%. The

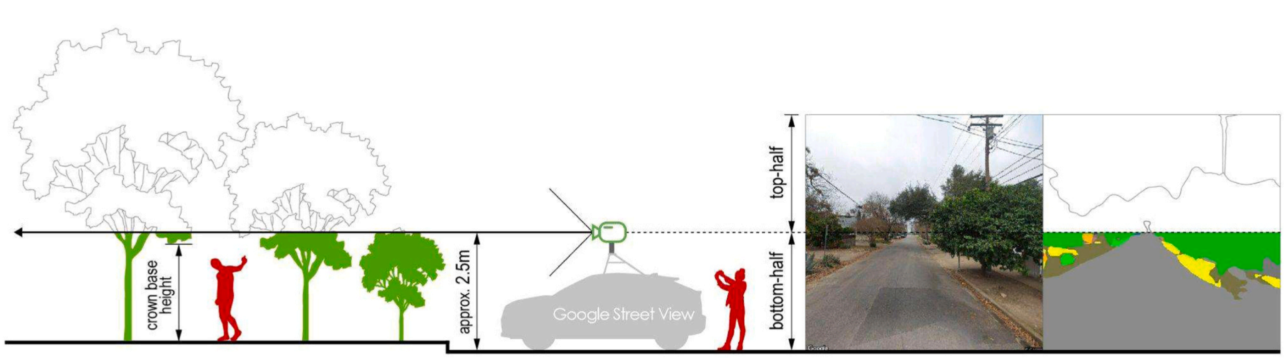


Fig. 3. Google street view camera and bottom-half imagery.

Table 2
Negative binomial regression results for the associations of different tree measurements with violent street crime.

Dependent variable	Data Source for Tree Distribution											
Number of violent street crimes	Model Group 1						Model Group 2					
	M1-1 Aerial Image		M1-2 Street View Image		M1-3 Tree Inventory		M2-1 Aerial Image		M2-2 Street View Image		M2-3 Tree Inventory	
(Intercept)	-9.149 (0.581)	* **	-8.948 (0.576)	* **	-8.992 (0.58)	* **	-8.062 (1.459)	* **	-7.757 (1.453)	* **	-7.987 (1.439)	* **
Tree measurement	-2.241 (0.951)	*	-3.990 (1.501)	* *	-0.130 (0.043)	* *	-2.378 (1.029)	*	-3.321 (1.632)	*	-0.133 (0.047)	* *
Employment density	-0.101 (0.042)	*	-0.100 (0.042)	*	-0.104 (0.041)	*	-0.092 (0.043)	*	-0.094 (0.043)	*	-0.097 (0.042)	*
Population density	-6.602 (73.221)		0.843 (73.209)		8.148 (73.576)		125.826 (69.601)		134.119 (69.867)		136.393 (70.015)	
Black population density	6.690 (3.244)	*	7.017 (3.231)	*	6.108 (3.247)		4.403 (3.101)		4.934 (3.096)		3.920 (3.098)	
Median household income	-0.025 (0.015)		-0.025 (0.015)		-0.022 (0.015)		-0.036 (0.016)	*	-0.037 (0.016)	*	-0.034 (0.016)	*
(Lag) Employment density	0.310 (0.106)	* *	0.300 (0.106)	* *	0.272 (0.107)	*	0.211 (0.117)		0.205 (0.117)		0.179 (0.118)	
(Lag) Population density	-377.037 (144.901)	* *	-387.09 (143.827)	* *	-442.631 (146.794)	* *	-356.374 (152.745)	*	-378.562 (152.907)	*	-420.866 (156.153)	* *
(Lag) Black population density	97.484 (11.504)	* **	92.828 (11.426)	* **	96.052 (11.409)	* **	99.695 (11.322)	* **	96.108 (11.317)	* **	98.507 (11.227)	* **
(Lag) Median household income	0.063 (0.018)	* **	0.063 (0.017)	* **	0.060 (0.018)	* **	0.074 (0.019)	* **	0.077 (0.019)	* **	0.072 (0.018)	* **
Presence of residential use							-0.503 (0.216)	*	-0.518 (0.215)	*	-0.455 (0.217)	*
Presence of commercial use							1.143 (0.187)	* **	1.088 (0.188)	* **	1.144 (0.187)	* **
Presence of parks							-0.337 (0.271)		-0.350 (0.273)		-0.357 (0.268)	
Walk Score							-0.029 (0.017)		-0.033 (0.017)		-0.028 (0.017)	
Bus stop density							94.701 (75.455)		112.12 (74.581)		94.158 (74.939)	
Presence of surface parking							0.102 (0.226)		0.048 (0.228)		0.090 (0.225)	
Street type: Aves (ref: Blvds)							1.649 (0.514)	* *	1.545 (0.512)	* *	1.686 (0.512)	* **
Street type: Streets (ref: Blvds)							1.113 (0.382)	* *	1.138 (0.385)	* *	1.160 (0.382)	* *
AIC	1268.144		1266.635		1265.097		1230.865		1232.098		1228.219	
n	518		518		518		518		518		518	
LogLik	-623.072		-622.318		-621.548		-596.433		-597.049		-595.109	

Note: ***$p < 0.001$, **$p < 0.01$, *$0.01 \leq p < 0.05$; Length of street segment was used as an exposure variable.

average portion of tree images using GSV was 9.8%. The average size-weighted tree density from tree-inventory was 2.9 DBH/meter, which cannot be directly comparable across other tree measurements. The average median household income at the block group levels (n = 4) was $93,405, which is higher than the city average ($75,752). The average Walk Score was 90.9, which indicated that the areas were "Walker's Paradise" according to the Walk Score criteria (90−100).

3.2. Regression results

3.2.1. Tree measures using all trees

Table 2 shows the negative binomial regression results using violent street crimes for Group 1 and 2 models. All three tree measurements in Group 1 models were associated with reduced violent street crime incidences, after adjusting for employment and population density, black population density, median household income, and their spatially lagged variants (M1–1 ~ M1–3). A one-percentage point increase in tree-aerial and tree-GSV was associated with 2.3% ≈ [1-exp (−2.378/100)]× 100 decrease and 3.3% decrease in violent street crime rate, respectively. A 10-percentage point increase in size-weighted tree density from tree-inventory was associated with a decrease in violent street crime rate by 1.3%. In terms of socio-demographic variables, higher employment density and higher median income were associated with fewer crimes at $p < 0.05$ and $p < 0.1$, respectively. Black population density was associated with more crimes at $p < 0.1$. All the spatially lagged measures showed strong associations with violent street crimes.

In Group 2 models, all three tree measures remain statistically significant predictors after adding the built environment control variables. Regarding the built environment variables, having commercial land use was associated with an increase in violent street crime while having residential load use was associated with a decrease in violent street crime. Compared to boulevards, avenues and streets tended to have more violent crimes.

Group 1 and 2 models for property street crimes are shown in Table 3. In Group 1 models for property street crime (M1–4 ~ M1–6), all tree measures were statistically significant with negative coefficients after adjusting for socio-demographic-related control variables, which was consistent with the results obtained for violent street crime. While employment and residential density, as well as their spatially lagged variables, were found to be significant factors in predicting violent street crime, they did not show a significant relationship with property street crime.

In Group 2 models for property street crime, three image-based measures remained significant (M2–4 ~ M2–6) even after controlling for the additional built environmental control variables. The significant land use variables were different from the case of violent crimes: the presence of residential land use was not a significant predictor while the presence of parks was significantly but negatively associated with property street crime. After including all control variables, a one-percentage point increase for tree-aerial and tree-GSV were associated

Table 3
Negative binomial regression results for the associations of different tree measurements with property street crime.

Dependent variable	Data Source for Tree Distribution					
Number of property street crime	Model Group 1			Model Group 2		
	M1-4 Aerial Image	M1-5 Street View Image	M1-6 Tree Inventory	M2-4 Aerial Image	M2-5 Street View Image	M2-6 Tree Inventory
(Intercept)	-7.836 (0.438) ***	-7.707 (0.438) ***	-7.946 (0.44) ***	-7.573 (1.247) ***	-7.250 (1.25) ***	-7.918 (1.246) ***
Tree measurement	-2.771 (0.805) ***	-4.527 (1.273) ***	-0.081 (0.034) *	-2.859 (0.851) ***	-3.942 (1.361) **	-0.081 (0.036) *
Employment density	-0.033 (0.035)	-0.03 (0.035)	-0.039 (0.035)	-0.019 (0.034)	-0.021 (0.034)	-0.025 (0.034)
Population density	89.913 (54.65)	79.418 (54.92)	100.369 (55.295)	78.820 (56.495)	86.636 (56.868)	83.324 (56.996)
Black population density	-0.005 (2.908)	0.378 (2.899)	-0.166 (2.947)	-1.390 (2.88)	-1.114 (2.887)	-1.431 (2.906)
Median household income	-0.007 (0.012)	-0.007 (0.012)	-0.005 (0.012)	-0.017 (0.013)	-0.017 (0.013)	-0.016 (0.013)
(Lag) Employment density	0.048 (0.095)	0.063 (0.095)	0.039 (0.097)	0.024 (0.104)	0.032 (0.104)	0.043 (0.105)
(Lag) Population density	-59.972 (115.28)	-62.275 (114.823)	-129.273 (116.9)	46.161 (120.827)	47.620 (121.441)	18.533 (123.13)
(Lag) Black population density	58.681 (10.544) ***	52.432 (10.498) ***	54.145 (10.618) ***	53.592 (10.549) ***	48.518 (10.603) ***	48.075 (10.595) ***
(Lag) Median household income	0.041 (0.014) **	0.041 (0.014) **	0.040 (0.014) **	0.048 (0.015) **	0.050 (0.015) ***	0.047 (0.015) **
Presence of residential use				-0.052 (0.181)	-0.096 (0.181)	-0.002 (0.184)
Presence of commercial use				0.596 (0.16) ***	0.565 (0.162) ***	0.594 (0.161) ***
Presence of parks				-0.632 (0.237) **	-0.614 (0.24) *	-0.713 (0.238) **
Walk Score				-0.012 (0.014)	-0.016 (0.014)	-0.009 (0.014)
Bus stop density				55.362 (66.459)	70.022 (66.191)	62.122 (66.805)
Presence of surface parking				0.546 (0.198) **	0.448 (0.201) *	0.561 (0.199) **
Street type: Aves (ref: Blvds)				1.072 (0.431) *	0.880 (0.432) *	0.818 (0.435)
Street type: Streets (ref: Blvds)				0.879 (0.315) **	0.898 (0.319) **	0.857 (0.319) **
AIC	1650.031	1649.591	1656.804	1631.477	1635.159	1637.968
n	518	518	518	518	518	518
LogLik	-814.015	-813.796	-817.402	-796.739	-798.579	-799.984

Note: ***p < 0.001, **p < 0.01, *0.01 ≤p < 0.05; Length of street segment was used as an exposure variable.

Table 4
Negative binomial regression results for the associations of tree size and view-obstructive characteristics with both violent and property street crimes.

Dependent variable	Data Source for Tree Distribution				
Number of violent street crime	(Model Group 3) Street View Images	(Model Group 4) Tree Inventory			
	M3-1 Tree image coverage in Bottom-Half	M4-1 Small tree density (DBH ≤10 cm)	M4-2 Small-medium tree density (DBH ≤ 20 cm)	M4-3 Medium-large tree density (DBH ≥ 30 cm)	M4-4 Large tree density (DBH≥40 cm)
Tree Measurement	-25.434 (10.27) *	0.338 (3.163)	-0.441 (1.792)	-7.128 (2.678) **	-13.575 (4.043) ***
AIC	1230.143	1237.12	1235.778	1229.018	1224.622
n	518	518	518	518	518
LogLik	-596.072	-599.56	-598.889	-595.509	-593.311
Dependent variable	Data Source for Tree Distribution				
Number of property crime	(Model Group 3) Street View Images	(Model Group 4) Tree Inventory			
	M3–2 Tree image coverage in Bottom-Half	M4–5 Small tree density (DBH≤10 cm)	M4–6 Small-medium tree density (DBH ≤20 cm)	M4–7 Medium-large tree density (DBH ≥ 30 cm)	M4–8 Large tree density (DBH≥40 cm)
Tree Measurement	-13.046 (7.194)	0.908 (2.697)	3.427 (1.465) *	-6.344 (2.16) **	-9.982 (3.063) **
AIC	1639.239	1643.892	1637.988	1634.616	1631.834
n	518	518	518	518	518
LogLik	-800.619	-802.946	-799.994	-798.308	-796.917

Note: ***p < 0.001, **p < 0.01, *0.01 ≤p < 0.05; All models were conducted after controlling for socio-demographic and built environment variables; Length of street segment was used as an exposure variable.

with a 2.8% decrease and a 3.9% decrease in property crime rate, respectively. A 10-percentage point increase in size-weighted tree density from tree-inventory was associated with a decrease in property street crime rate by 0.8%.

3.2.2. Tree measures reflecting view-obstructive characteristics

Table 4 shows the results of how tree size and view-obstructive characteristics are associated with violent and property street crimes after controlling for socio-demographic and built environment variables. Tree-GSV and tree-inventory were further segmented to reflect the view-obstructive characteristics and tree size in Group 3 and 4 models respectively. The statistical significance of the coefficient estimates for the intercept and control variables remained consistent, with only negligible variations in their magnitude and sign when compared to Tables 2 and 3. For brevity, they are omitted from display. The tree-GSV from bottom-half of images (tree-GSV-bottom) was strongly associated with reduction in violent street crime. Specifically, a one-percentage point increase in tree-GSV from bottom-half of images was associated with a 22.5% decrease in violent street crime rate in Model 3–1. Tree density based on different DBH sizes from tree inventory were also associated with reduced crimes if it was measured from trees with DBH $\geq$ 30 cm or DBH $\geq$ 40 cm (M4–3 and M4–4).

The regression results for property street crimes showed diverging results from those for violent street crimes regarding tree size and its view-obstructive characteristics. As shown in Model 3–2, tree-GSV-bottom was a marginally significant predictor of property crimes at $p < 0.1$. The small-medium tree density as measured in tree-inventory in Model 4–6 was associated with increased property street crimes. A one-percentage point increase in small-medium tree density (DBH $\leq$ 20 cm) was associated with an increase in property street crime rate by a 3.5% $\approx [\exp(3.427/100) - 1] \times 100$. The larger trees (i.e., DBH $\geq$ 30 cm and 40 cm) consistently showed negative association with decrease in property street crimes. The direction and significance of other control variables were mostly consistent with what we discovered in prior models.

4. Discussion

This study aimed to investigate how urban trees affect violent and property crimes that occur on the streets in downtown Austin, TX (US). It addressed gaps in the literature in multiple ways. First, the literature has paid relatively little attention to the relationship between environmental factors and safety and street crime in downtown areas. Prior research primarily explored criminal activity from an entire city or in residential settings (Hipp et al., 2021; Sohn, 2016). This study provides insights on how urban trees can help reduce street crimes and their adverse impacts on downtown users. Second, we used different measurements of tree characteristics to explore their associations with street crime comprehensively. Previous studies usually relied on a single data such as satellite imagery (Troy et al., 2012). However, the canopy cover measured from aerial imagery cannot fully capture the 3-dimensional trees from eye-level views and is limited in accurately estimating the number and height of the trees (Li et al., 2018). By using street view images and tree inventory, this study can help overcome the limitations of using only one type of measurement of trees to reflect the characteristics of trees in relation to street crime. Importantly, the literature that used tree measurements derived from image sources were unclear as to how well the image-based measurements represent the actual ground truth. This study compared tree inventory data to other image-based tree measurements through correlation and regression analyses to provide more insights. Finally, we explored the potential role of view-obstructive characteristics of trees on two types of street crime. Specifically, we used the proportion of trees that appear in the bottom-half of GSV images and multiple DBH thresholds (i.e., 10, 20, 30, and 40 cm) from tree inventories as proxy measures of potential view-obstructiveness. They offer insights on how small trees or tree visibility below eye level may lead to a decrease in natural surveillance and an increase in opportunities for criminal activities, ultimately leading to higher crime rates, particularly property crimes.

Our findings add to the body of evidence on the role of urban trees in reducing the risks of criminal activity and urban safety. While many studies have focused on residential settings and widely reported that both private and public trees can help reduce crime (Coley et al., 1997; Troy et al., 2012), few have focused specifically on downtown areas which are, unlike residential areas, often densely developed and bustling with people. This study can enhance our understanding of the 'tree--crime' relationships in retail or business-oriented settings by focusing on urban downtown. In order to improve downtown security, many cities have historically adopted various policy solutions, including strict law enforcement and environmental design (Crowe, 2000). Although these efforts to date have often been through strengthening law enforcement, recent efforts for improving personal safety and security have been associated with the dual goals of crime reduction and increased urban livability and quality of life (Tretter, 2013). Our findings suggest that urban vegetation in downtown areas is an important contributor to attracting pedestrians on the streets and increasing urban vitality as well as preventing crime.

The three measures of trees generally showed consistent association with reduced crimes with some variations depending on the type of crime. This variation was most pronounced with tree-inventory. When tree size was considered in Model Groups 3 and 4, our results showed that medium-large tree density (i.e., DBH $\geq$ 30 cm) showed consistent and the most significant associations with a decrease in both violent and property crimes among all tree measures used in this study. This is consistent with previous studies, indicating that large trees can provide greater visual access and natural surveillance (Lin et al., 2021). However, the density of medium-sized trees (DBH $\leq$ 20 cm) was found to be associated with increased property street crime (Model 4–6). The positive association between the number of small trees and property crime at street level, but not violent crime, aligns with our current understanding and the existing literature, which suggests that effective surveillance is more likely to deter property crime than violent crime (Piza et al., 2019). This finding is also in line with previous research that has shown that small trees are more likely to impede views than large trees (Donovan & Prestemon, 2012).

The findings from the analysis of the bottom-half of street view images were consistent with the results from the analysis of tree-inventory data. However, it is unclear whether this is due to a higher concentration of small and large trees in the bottom-half of street view images. The study assumed that the tree images around and below eye-level could be used as a proxy for measuring the potential obstructiveness of view. The proportion of trees shown in the bottom-half of GSV did not have a significant relationship with property crime, suggesting that the overall benefits of trees in reducing property crime might be negated by their view-obstructiveness. However, the analysis showed that the tree-GSV-bottom variable remained statistically significant in relation to violent crimes, and interestingly, became a stronger factor. This could be because trees at and below eye-level may create a more immersive and engaging experience for viewers, with positive effects on mental health and well-being, such as reducing stress, improving mood, and increasing visual access. Furthermore, the screening effect of the foliage below eye-level may serve as a visual mask that covers stressful urban stimuli, potentially reducing the likelihood of violent crimes (Kaplan & Kaplan, 1989).

4.1. Planning implications

Many downtowns or other densely developed central urban areas often have high crime rates, which is one of the main obstacles to the economic redevelopment of downtown districts. While the benefit of urban trees in reducing crimes is increasingly recognized, many downtowns often lack sufficient tree canopy (Danford et al., 2014).

Furthermore, urban trees provide many other benefits such as filtering air and water, controlling stormwater, and conserving energy (Nowak et al., 2016; The City of Austin, 2013). To create a more sustainable city, the Austin Climate Equity Plan (2021) has adopted the urban forest plan to increase citywide tree canopy cover from 35% to 50% by 2050 through preserving existing canopy cover and increasing tree planting. However, the Imagine Austin Comprehensive Plan regards trees primarily as elements for green infrastructure, green street design, and sport & recreation, ignoring their important function, crime reduction and safety aspects (Austin City Council, 2018). The public safety policies in the plan only concern police forces, public safety services, education, facilities, lighting, density, accessibility and street surveillance for overall city scale. As shown in the results, the city needs to consider trees as crime reduction elements to perform more effective green and public safety strategies. In addition, new/existing planting location and tree types/size/height should be carefully selected depending on previous or potential crime types.

It is also challenging to increase tree canopy coverage within densely developed downtown areas. Previous studies found that population density and tree canopy coverage is likely to be inversely correlated (Koo et al., 2019). Some of the reasons include the lack of space for planting trees in densely developed urban areas and the insufficiency of conditions and resources (e.g., nutrients, sunlight, etc.) for existing trees to grow. Though with narrow sidewalks and limited planting space in downtown areas, new planting spots can be identified by set-back regulations for new development, zoning change, and preserving/managing current trees when implementing the green and safety strategies.

4.2. Methodological implications

The findings suggest that three measurements of trees in this study have distinct strengths and limitations that can be used strategically to understand and manage city forests as well as to see crime prevention benefits. First, the overhead view perspective of tree-aerial images is convenient to measure tree canopy because of its geographic and temporal availability. However, some trees have crowns that extend into both private and public spaces, making it difficult to discern between public and private trees. It can be also challenging to evaluate certain details, such as whether or not trees have view-obstructive characteristics.

Unlike tree-aerial images, tree-GSV is captured from a pedestrian's eye level perspective. This enables users to estimate the position of trees in their field of view, such as they appear above or below the usual sightline of people at around 2 m above the ground. However, tree-GSV does not have intrinsic ways to distinguish trees on public right-of-way from those in private parcels. Furthermore, tree-GSV only includes trees that are visible from the road and exclude any trees that are occluded from the camera by other large objects, such as another tree. Another important caveat is that PSPNet (i.e., the computer vision model used in this study) does not distinguish individual trees. This implies that the trees detected in street view images will be lumped together, and it is not possible to distinguish smaller trees from larger trees; it simply lets us know how much of the scene is trees. This indicates that if a street segment has a high tree image coverage shown in the bottom-half of the images, it does not necessarily mean that there are many small trees. It can also be the result of large trees with thick trunks or crowns stretching further down below the sightline.

Finally, the inventory data is the closest to the ground truth information on tree location and caliber, as it is manually measured on the field. This data records information for individual trees separately. Because the inventory data in this study measured only public trees and excluded those on private lands, the scope is innately different from Tree-GSV, which can contain both public and private trees. This is illustrated by the finding that there were 57 street segments in which tree-GSV was greater than zero (i.e., some amounts of trees were visible in GSV images) but had no trees at all according to tree-inventory (i.e., no trees on the public right-of-way). Future studies can adopt citizen science approaches by engaging volunteers in tree data collection, including private trees and quality of trees.

4.3. Limitations

The present study is subject to several limitations. First, this study is subject to generalizability concern because only one downtown in a U.S. city was examined in this study. Future studies should use multiple downtown areas in U.S. cities to explore the benefits of trees in relation to safety. Second, causality cannot be determined in this study as it is unable to reflect the possible effects of changes in tree conditions, such as planting, growing, or removing trees, on changes in street crime. Further studies could employ time-series data and quasi-experimental approaches to explore this relationship. Third, the data used in this study was collected at different time periods, which may introduce some variation in results. For example, tree canopy coverage was measured in 2014, while street view trees were based on images taken in, on average, 2020 in this study. Additionally, 6-year aggregate data was used to analyze crime due to the rarity of crime events at the street segment level within short-term time frames (Lee et al., 2023). By utilizing 6-year aggregate data, this study was able to mitigate the impact of annual fluctuations in crime events and capture a sufficient number and variation of crime events. However, future studies should use more recent and consistent data sources.

It is also crucial to acknowledge that there are inherent accuracy challenges when it comes to classifying of aerial and street view imagery. As previously mentioned, the pixel-wise accuracy of PSPNet is currently limited to 80.04%. However, it is important to note that enhancing the model's accuracy beyond this point would necessitate retraining it with a new dataset and additional computational resources, which were not accessible at the time. Moreover, while we used DBH scales and the tree coverage in the bottom-half of GSV images as proxy measures of potential view-obstructiveness, it is important to acknowledge that there was no on-the-ground validation of the view-obstructive effects of small diameter trees and tree coverage in the bottom-half of GSV images in this dataset. This constraint should be considered when interpreting the findings. Future studies should consider using LiDAR data to account for tree height and to address the potential mediating effect of tree height and view-obstruction on the relationship between trees and crime. Finally, although we utilized diverse sources to quantify the tree characteristics, we were unable to capture factors such as tree health or aesthetics, which are important indicators, as suggested by the "broken window theory," that the street is being monitored and maintained (Lee et al., 2023). Despite these limitations, the findings of this study provide valuable insights into the potential role of urban trees in crime prevention and suggest the need for further research in this area.

5. Conclusions

This study has provided evidence that urban trees are beneficial in reducing street crime in downtown Austin, TX, which could inform evidence-based downtown redevelopment strategies to improve livability and safety. The findings suggest that regardless of the source of tree data, trees are associated with reduced street crimes. We also found that larger trees were significantly associated with crime prevention, while smaller trees showed no significant association or were associated with more crimes, depending on the types of crime. Additionally, although the bottom-half of GSV images with tree coverage may have obstructive qualities, the presence of trees around and below eye-level can still have a positive impact on urban environments by promoting mental well-being and reducing violent crimes. This highlights the importance of careful consideration of the location and size of trees in urban planning and design to optimize their benefits and minimize potential drawbacks. The study's results add to the literature by proposing that urban trees, as a relatively low-cost intervention, can be a new partner in the fight against downtown street crime. Furthermore, the study highlights the significance of tree DBH and the utilization of the bottom-half of GSV images with tree coverage as a proxy measure for both tree size and the view-obstructive nature of trees.

CRediT authorship contribution statement

Sungmin Lee: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. **Bon Woo Koo**: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Writing – original draft, Writing – review & editing. **Youjung Kim**: Conceptualization, Data curation, Investigation, Visualization, Writing – review & editing.

Declaration of Competing Interest

We have no conflicts of interests to disclose.

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