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Breakthroughs in Epidemiology

Tree canopy cover and injurious pedestrian falls: a location-based case-control study

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Abstract

Despite about half a million injurious pedestrian falls occurring annually in the United States, prevention of pedestrian falls is under studied. Sidewalk damage from street trees is a known risk for falls; however, tree canopy cover might reduce falls in summer months by lowering ambient temperatures. We conducted pilot research to assess whether emergency medical services (EMS) data could be used to implement a multi-city, location-based case–control study investigating the association between tree canopy cover and locations of injurious pedestrian falls. Case locations ($n = 497$) were places where EMS responded to a pedestrian fall occurrence between April and September of 2019. Matched control locations ($n = 994$) were selected from intersections, street segments, and ramp segments that existed in 2019. Percent tree canopy cover was measured within a 100-m radial buffer of each location. Median tree canopy coverage at fall locations was 8%, compared to 14% for control locations. In adjusted analyses, higher tree canopy cover was inversely associated with fall locations (adjusted OR across the inter-quartile range of canopy cover = 0.57; 95% CI, 0.45-0.74), suggesting higher tree canopy cover is associated with lower pedestrian falls risk. Methodological challenges and solutions to implementing and interpreting the location-based, case–control design with EMS data are discussed.

Key words: pedestrian safety; location-based case–control study; pedestrian injury; tree canopy cover.

Introduction

Falls and fall-related injuries represent a substantial public health burden, particularly for older adults.[1] There is a robust body of research on causes and prevention of falls occurring indoors, but causes of falls occurring outdoors are understudied.[2-4] Analyses of the 1997 to 2010 National Health Interview Survey data found that an estimated 518 000 fall injuries requiring at least some medical attention occurred on sidewalks or streets annually in the United States.[3] Prior work identified 118 520 Emergency Medical Services (EMS) responses for injurious falls occurring on streets and sidewalks within the 2019 National Emergency Medical Services Information System (NEMSIS) database.[5]

Unlike indoor falls, which are influenced by an individual's risk factors and poor health status, outdoor falls are often associated with health-promoting activities (eg, walking, gardening), and are particularly influenced by physical aspects of the environment.[4,6] While fall risk is well known to be associated with snow and ice, there is an emerging literature showing that fall risk is also associated with high temperatures.[3,7-9] High temperatures are thought to influence fall risk due to the negative effects on human physiology[10] and the degrading effects of heat on sidewalk and road surfaces.[11] Trees lower ambient temperatures and improve thermal comfort for pedestrians, which may reduce falls occurring on streets and sidewalks.[12-14] A prior study in urban areas of Marin County, California, found an inverse association between tree canopy cover and falls during leaf on seasons, but was limited by its ecological study design.[14] Despite these findings, a frequent concern in communities receiving street trees and in popular media reports on tree planting campaigns, is that tree detritus and sidewalk damage from tree roots increases the risk of pedestrian falls.[15,16]

Pedestrian falls are an epidemiologically rare event for which methods to ascertain cases and collect data at a large scale have not been previously described. As such, epidemiological studies of pedestrian falls are challenging and few have been conducted. Because environmental risk factors are likely to be in close proximity to the location of a pedestrian fall, a location-based, case-control study is a useful study design option.[17] Here

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we report on a pilot study to: (1) evaluate and establish methods for using EMS administrative and clinical data to implement a multi-city, location-based, case-control study; and (2) use this design to examine the association between tree canopy cover and locations of pedestrian injuries from falls.[17]

Methods

Study population

This pilot study used data from ESO Solutions, Inc. (ESO, Austin, TX), one of the largest third-party logistics and data companies providing services to EMS, including the collection and storage of EMS data in the NEMSIS standard format and submission of those data to NEMSIS.[18] Data on the location of the EMS unit that encountered the patient are stored by ESO but are not available in the NEMSIS public release dataset. Data on the address to which the EMS unit was dispatched come from the EMS Computer Aided Dispatch systems; however, responding EMS clinicians can enter corrected addresses into the record if the address provided by the dispatcher needs refining. ESO geocodes the reported location of the health event to longitude and latitude coordinates using Geocodio (Arlington, VA). ESO also links a portion of its EMS records to hospital admission and discharge records.[19]

Data for 2019 were used in this research to avoid pandemic related impacts on pedestrian behavior and EMS responses.[2] ESO's 2019 health records included data from 8 340 148 EMS activations, of which 704 300 were linked to hospital records. This pilot study focused on EMS data for patients with linked hospital data, for several reasons, including the following: to assess whether hospital admission/discharge diagnosis data could be used as an alternative method for identifying fall patients; and to plan for studies of etiological heterogeneity by injury severity and whether the patient was admitted to the hospital or discharged from the ED.[17,20]

Using previously developed methods, ESO identified all EMS responses to pedestrian falls on streets and sidewalks that occurred between April 1st and September 30th of 2019 ($n = 15\,357$).[2] Of these responses, linked patient hospital discharge data were available for 2385 patients and of these patients, 908 patients were excluded because EMS reported involvement of alcohol or drugs in the fall.[21] From the remaining 1477 patients, 500 were randomly selected and data on the reported longitude and latitude location of the fall were analyzed for this pilot study. This sample size was selected because it provided reasonable statistical power and was of a manageable scale if manual inspection of the locations was needed.

Processing of the ESO longitude and latitude data

Manual inspection of the location data provided by ESO found a mix of locations on center lines, intersection centroids, building footprints and sidewalks. The longitude and latitude coordinates for 34 locations were located on a parking lot or on residential or commercial property near a street or sidewalk. For these cases, the location was attributed to the nearest street and its center line. The control-location selection process (see below) chose random points along street center lines or used intersection centroids. Street center lines and intersection centroids are likely to have lower tree canopy cover than locations on sidewalks, and so it was possible that there were systematic differences between selected control locations and reported case locations. As such, the longitude and latitude data for the reported case locations were snapped to the closest street center line or intersection centroids (median snapping distance 15.4 m). As street center lines serve as Census tract boundaries, to ensure that the locations fell within a tract, the case locations were then offset from these center lines or centroids by 1-foot in a random direction perpendicular to the center line. A sensitivity analysis was performed using case location data as directly provided by ESO, prior to being snapped to the street center line or intersection centroid.

Location-based, case–control study design

In location-based case-control studies, described in detail previously,[17] longitude and latitude coordinates for locations where patients experienced events (eg, falls) are treated as "cases" and are compared to matched control locations. For the present work we focused falls occurring within Metropolitan Statistical Areas (MSA). Of the 500 pedestrian falls provided by ESO, two cases did not fall in a 2020 Census MSA and were excluded. One case fell in a body of water and was also excluded. There were three locations at which multiple pedestrians fell (2 per location) on different dates. The 497 eligible case locations were located across 44 MSA. The 2 095 259 intersections, 3 896 541 road segments, and 54 704 highway exchange/ramp segments in these MSA, as defined by the 2021 TIGER/Line Roads data files as of January 1, 2019, constituted the eligible street infrastructure from which control locations were selected.

Two-stage sampling plan for selecting control locations

In stage 1, a randomly selected point was defined along the street center line for each street segment or ramp in the 44 MSA. Intersections were defined at the location where street segment center lines intersected. Each point was initially defined by its longitude and latitude coordinates. Then to ensure that these points fell within a Census Tract, the points were shifted 1-foot perpendicular to the center line, with the direction selected randomly. Intersections points were also shifted by 1-foot by first creating a 1-foot radius circle around each point, and then selecting a random point on the circumference of the circle. These shifted point locations comprised the population of all possible control locations ($n = 6\,046\,504$).

In stage 2, the pool of locations eligible to be selected as control locations in the 44 MSA was defined street segments, and ramp segments, on which a case location did not occur by the end of follow-up as of December 31, 2019 ($n = 6\,046\,010$).[22] The point locations defined in stage 1 associated with these intersections, street segments, and ramp segments comprised the pool of possible eligible control locations for each case location. The pool of locations eligible to be selected as controls for each case was then further defined via individual matching to the case location on: (1) roadway type (ie, segment, intersection, ramp); (2) road class classification (eg, primary road, secondary road, local road), with the highest road class entering an intersection used as the matching value; (3) county; and (4) county-specific quintile of Census tract-level population density.[17] For each case location, two control locations were then randomly selected from the pool of eligible control locations that met the matching criteria. For the three locations where two case events occurred on different days, a separate control location was selected for each of the six case events.[23,24] As discussed in Appendix S1, control location selection did not match on time related factors.

Road type and road classification are associated with pedestrian volume[25] and were expected to be associated with tree canopy cover.[17] Matching on county accounted for regional differences in urban design and zoning that affect pedestrian activity flows.[26] As population density is a key predictor of pedestrian traffic, matching on county specific quintiles of residential density increases the statistical efficiency of adjusting for proxy measures of pedestrian density.[27]

Exposure assessment

Tree canopy cover at case and control locations was measured using the National Land Cover Database for 2019, generated by the Multi-Resolution Land Characteristics (MRLC) consortium.[28] Data on the percent of land area covered by tree canopy are available for the entire continental US at a 30 × 30-m resolution. We measured the percent of land covered by tree canopy for 100-m radial buffers around case and control locations and performed sensitivity analyses for 250-m and 1 km buffers. Spatial statistics were used to calculate the percent of surface area covered by tree canopy.[29]

Covariates

An important confounder in pedestrian injury research is the number of pedestrians at a location that are at risk of experiencing an event.[30] As pedestrian count data and pedestrian traffic estimation models are not available in many areas, we used three key measures of neighborhood walkability for buffers around case and control locations: (1) the density of walkable destinations (number of retail businesses per km^2) using the National Establishment Time Series (NETS) dataset[31]; (2) intersection density (intersections per km^2, a measure of street connectivity) using 2021 TIGER/Line Road data files; and (3) population density (per km^2) using 2020 Census data. We have shown that neighborhood walkability measures can be used as a replacement for pedestrian count data as a covariate in studies of pedestrian safety.[27,32]

Differences in neighborhood composition, such as poverty rates, could influence the composition and fall risk profile of pedestrians at any given location.[33] Neighborhood-level socioeconomic variables may also be associated with sidewalk maintenance (eg, poorer in lower income areas) and where street trees have recently been planted (eg, new plantings being more likely in lower income areas).[34] We characterized the percent poverty and median household income using 2017-2021 American Community Survey (ACS) at the Census 2020 tract summary level. When a radial buffer included an area from two or more Census tracts, the tract-level data was weighted by the count of people or households in Census blocks whose centroids fell within the radial buffer. In instances when a radial buffer included area from two or more tracts but no Census block centroids fell within the radial buffer, the tract level-data were combined using aerial weighted interpolation to construct estimates for the radial buffer.[35]

ArcGIS Pro, version 3.4.0, was used for all geospatial analysis (ESRI, Redlands, CA).

Statistical analyses

Adjusted odds ratios (AOR) were estimated using conditional logistic regression (CLR).[36] Neighborhood characteristics were rescaled to the interquartile range (IQR) using the distribution of values from the control location observations. Tree canopy cover was also categorized into quartiles using the distribution of tree canopy cover across the control locations. AOR presented in the tables can be interpreted as the odds ratio comparing case locations to control locations whose neighborhood differed by the IQR, or quartile, of tree canopy coverage. In the location-based design, data are not available on risk factors for individuals, such as age, who did not fall at each selected control location. It is possible that individual-level risk factors exist that interact with tree canopy cover to shape risk. In this scenario, under the rare disease assumption, the location-based case-control AOR calculated for tree canopy cover is understood to estimate the weighted average of risk ratios for injurious falls that otherwise would be calculated for tree canopy cover among those with the individual-level risk factor and among those without the individual-level risk factor (Appendices S2, S3 and Figures S1, S2).[37,38]

Sensitivity analyses were performed by removing locations with an ambiguous segment or intersection roadway type assignment (n = 34 cases). There were six reported locations at which multiple pedestrians fell (two per location), with each pedestrian falling on a different date. Sensitivity analyses were conducted in which one case at these duplicate locations was removed from the analyses. All analyses were performed using R Statistical Software (v4.4.1; R Core Team 2024).

The protocol for this study was reviewed by the Columbia University Irving Medical Center IRB and was determined to be Exempt because Personal Health Information and Personal Identifying Information was not used in the research. As such Informed Consent procedures were not administered.

Table 1. Demographics for pedestrians who experienced a fall on a street or sidewalk, April 1 to September 30, 2019.

Characteristics	**N = 497[a]**
Age (years)	54 ± 22
Age groups	
0-17	20 (4.1%)
18-49	172 (35%)
50-64	122 (25%)
65+	179 (36%)
Unknown	4 (0.8%)
Gender	
Female	211 (43%)
Male	284 (57%)
Unknown	2 (0.4%)
Race or ethnicity	
Asian	10 (2.2%)
Black or African American	93 (20%)
Hispanic or Latino	33 (7.2%)
White	325 (70%)
Unknown	36 (7.2%)

[a]Mean ± SD; n (%).

Results

For the 497 pedestrians who experienced a fall on a street or sidewalk the average age was 54 years, with the majority (61%) of the pedestrians being 50 years or older (Table 1). The majority of locations of the pedestrian falls were located in the South (54%) US Census region, followed by the West (31%), Midwest (11%), and Northeast (5%). Primary diagnoses from hospital admission and/or discharge records were recorded for 430 of the fall patients, with 96 of them having a report of a fall noted in their ED admission, ED discharge or hospital discharge data fields. Most of the reported diagnoses related to likely consequences of a fall such as, lacerations, contusions and pain. Data on whether the patient was discharged from the ED or admitted to the hospital was available for 452 patients, with 85 of those patients being admitted to the hospital.

Table 2. Descriptive statistics of neighborhood characteristics for 100 meter radial buffers at case and control locations (N = 1491).

Neighborhood characteristics	Case, n = 497[a]	Control, n = 994[a]
Tree canopy cover (percent of land area covered by tree canopy)	8 (2-17)	14 (5-27)
Population density (per km^2)	1402 (478-2836)	1371 (673-2486)
Area poverty (percent of residents below federal poverty line)	13 (5-21)	8 (3-17)
Median household income ($)	64 091 (46 333-88 924)	72 879 (52 465-96 910)
Density of walkable destinations (per km^2)	64 (0-191)	0 (0-32)
Intersection density (per km^2)	64 (32-96)	64 (32-96)

[a]Median (IQR).

Case locations had a median of 8% tree canopy coverage compared to 14% for control locations (Table 2). Tree canopy coverage was negatively correlated with population density, area poverty, and density of walkable destinations and positively correlated with median household income (Table 3). After adjustment for matching factors (Table 4, model 1), percent tree canopy cover was significant and inversely associated with locations of pedestrian falls and remained so after further adjustment for neighborhood walkability metrics (model 2) and after additional adjustment for income related variables (model 3). Figure 1 depicts the odds ratios for locations of pedestrian falls by quartiles of tree canopy coverage after adjustment for matching factors and all neighborhood covariates. Compared to the first quartile of percent tree canopy cover the AOR for the second quartile was 0.84 (95% CI, 0.59-1.21), for the third was 0.55 (95% CI, 0.36-0.84) and the fourth was 0.32 (95% CI, 0.20-0.53).

Sensitivity analyses for larger neighborhood geographies showed the inverse association for tree canopy cover was consistent when a 250-m and a 1-km radial buffer were used. The results were similar in sensitivity analyses that used case locations as reported by ESO, without being snapped to the center line or intersection centroid (data not shown). Additional sensitivity analyses found similar results as the main analyses when ambiguous reported case locations (n = 34) were removed from the analyses, and when the six additional cases were removed because they occurred at the same location (n = 457, cases).

Discussion

This work demonstrates that large scale epidemiologic studies of pedestrian fall injuries can be conducted efficiently using EMS data for case-ascertainment. However, some additional geoprocessing of the EMS longitude and latitude data is required, as is some manual inspection of the locations. In addition, attention must be paid to accounting for possible systematic differences between control locations selected using street center line data and case locations defined by geocoded address locations. While not available in the NEMSIS public release data, location data on EMS encounters with pedestrian fall patients are available through EMS logistics support vendors, such as ESO Solutions, and through state EMS offices. Analyses of linked hospital data also demonstrate that admission and discharge diagnosis data have a low sensitivity for identifying pedestrian injuries by falls.

The analyses find locations where injurious pedestrian falls occurred during leaf on seasons have lower tree canopy cover than matched control locations. To our knowledge, this is the second study to show an inverse association between tree canopy cover and pedestrian falls.[14] The protective effect for tree canopy cover on falls in these two studies may ultimately be explained by the effects of trees on lowering ambient temperatures, as an emerging literature suggests that higher ambient temperatures are a risk factor for outdoor falls.[3,7,8,12]

There are several other possible explanations for the observed inverse association between tree canopy cover and locations of pedestrian falls. Prior work found that pedestrian walking speed is lower in areas with higher Normalized Difference Vegetation Index, a measure of green space.[39] This suggests that people may walk more slowly in neighborhoods with greater tree canopy cover, potentially reducing the risk of falling and/or lowering the risk of injury from a fall. Additionally, while analyses adjusted for poverty rate and median household income, it is possible that residual confounding with these measures, or other dimensions of area socioeconomic status could have contributed to the observed associations. However, since the results of analyses with and without adjustment for socioeconomic variables were so similar it is unlikely that there is major confounding effect by area socioeconomic conditions.

In addition to the emerging literature showing higher outdoor temperatures being associated with falls, high temperatures are also associated with syncope and heat illness.[2,40] Syncope and heat illness often result in injury from falls and clinically can appear as mimics of each other and as mimics of mechanical falls, particularly among older adults.[40] Climate change–related rises in temperature are likely to cause increases in pedestrian falls, and

Table 3. Spearman correlations between neighborhood characteristics.

	Tree canopy cover	Population density	Median household income	Area poverty	Density of walkable destinations	Intersection density
Tree canopy cover						
Population density	−0.05*					
Median household income	0.18*	−0.05				
Area poverty	−0.11*	0.40*	−0.60*			
Density of walkable destinations	−0.34*	0.19*	−0.08*	0.16*		
Intersection density	−0.04	0.15*	−0.06*	0.10*	0.13*	

Neighborhood characteristics were assessed for a 100-m buffer around case and control locations.
*$P < .05$.

Table 4. Associations across the IQR range of tree canopy cover with locations of pedestrian falls (100-m radial buffer).

Characteristic	Model 1 (*n* = 497, Cases)		Model 2 (*n* = 497, Cases)		Model 3 (*n* = 497, Cases)		Model 4 (*n* = 301, Cases)	
	OR (95% CI)	P value	OR (95% CI)	P value	OR (95% CI)	P value	OR (95% CI)	P value
Tree canopy cover (%)	0.37 (0.29-0.47)	<.001	0.53 (0.41-0.67)	<.001	0.57 (0.45-0.74)	<.001	0.54 (0.39-0.75)	<.001
Population density (per km^2)			1.05 (0.98-1.12)	.20	1.05 (0.97-1.12)	.20	1.09 (1.0-1.18)	.06
Density of walkable destinations (per km^2)			1.17 (1.12-1.22)	<.001	1.17 (1.12-1.22)	<.001	1.20 (1.13-1.27)	<.001
Intersection density (per km^2)			0.64 (0.54-0.75)	<.001	0.64 (0.54-0.76)	<.001	0.59 (0.46-0.75)	<.001
Area poverty (%)					1.25 (1.02, 1.53)	0.04	1.20 (0.92, 1.56)	.20
Median household income (thousands)					0.83 (0.65-1.05)	.11	0.90 (0.66-1.22)	.5

Data were analyzed using conditional logistic regression. Model 1: adjusted for matching factors. Model 2: adjusted for matching factors and neighborhood walkability metrics. Model 3: adjusted for matching factors, neighborhood walkability metrics and neighborhood socioeconomic factors. Model 4: case locations for patients aged 50 or older and matched control locations, adjusted for matching factors, neighborhood walkability metrics and neighborhood socioeconomic factors. All variables are scaled to the IQR using the control sample to facilitate comparison. For Census variables, when a radial buffer included area from two or more tracts but no Census block centroids fell within the radial buffer, the tract level-data were combined using aerial weighted interpolation to construct estimates for the radial buffer.

in fall injuries arising from episodes of syncope and heat illness.[41] Episodes of syncope and heat illness, and associated fall injuries, can also be identified using EMS data and are likely amenable to study using a location-based, case-control design.[2] Additional data on the net effect of tree canopy cover on pedestrian falls, syncope, and heat illness occurring on streets and sidewalk are needed.

Limitations

The study did not assess possible mediators of links between tree canopy cover and locations of falls, such as differences in temperature at case and control locations or tree related damage to sidewalks and curbs. In addition to possible causal mediation by differences in temperature, it is possible that the inverse association between tree canopy cover and locations of pedestrian falls could be explained by displacement effects related to differences in temperature.[42] With displacement effects, falls that otherwise would have occurred later, instead occurred sooner due to higher temperatures in low-canopy areas. That is, tree canopy cover influenced the timing and location of a fall for an individual who was "doomed" to experience a fall. This is a possibility that cannot be investigated with a case–control design. In the context of the finding of an inverse association between tree canopy cover and locations of falls, tree related damage to sidewalks and curbs would most likely act as a suppressor variable (AKA an inverse mediator, inconsistent mediator or competitive mediating variable), and adjustment for these variables would increase the magnitude of the observed inverse association.[43]

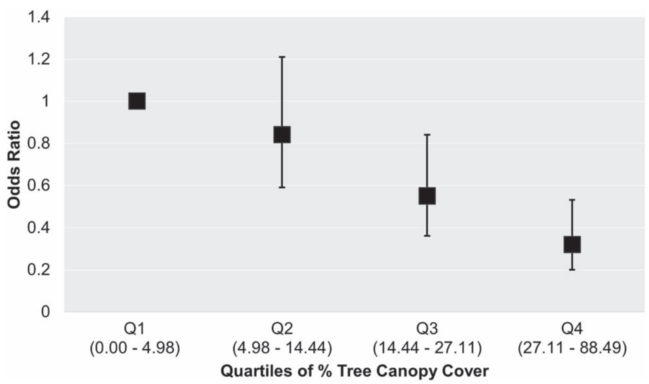

Figure 1. Odds ratios for locations of pedestrian falls on streets and sidewalk by quartiles of percent tree canopy cover. Circles and error bars represent ORs and 95% confidence intervals. The range of tree canopy cover (%) are displayed for each quartile (eg, Q1: 0.00-4.98). Data were analyzed using conditional logistic regression, the lowest quartile of tree canopy cover (Q1) is considered the reference level. The analysis is adjusted for matching factors, population density, area poverty rate, median household income, intersection density, and density of walkable destinations. The number of case locations and control locations for each quartile are as follows: Q1: Cases = 203, controls = 249; Q2: Cases = 141, controls = 248; Q3: Cases = 90, controls = 248; Q4: Cases = 63, controls = 249.

Our pilot study may be limited by measurement error in the health outcomes, exposure measures and covariates. Locations were eligible to be a control location if they were associated with a street or ramp segment or intersection upon which one of the 497 case pedestrian falls did not occur. It is possible however that pedestrian falls not included in this case series occurred on one of the segments or intersections associated with chosen control locations. However, the 2019 NEMSIS data set includes 118 520 EMS responses for pedestrian falls across 44 states and 3 territories; which constitutes a rare event compared to the 6 046 505 segments, ramps and intersections that were eligible for control selection in our study. In addition, for segments and ramps, the pool of possible control locations was comprised of a randomly selected longitude/latitude coordinate on the segment or ramp. Thus, it is highly unlikely that a location of a pedestrian fall that was not among the analyzed cases, was randomly selected as a control location.

Measurement error in exposure assessment may also have been induced by the geocoding of the locations that EMS encountered the patient. Some of these reported locations may have been the nearest street address to the actual occurrence of a fall, such that falls occurring in open areas were attributed to a nearby address. Furthermore, falls that occurred at intersections were often reported as being at the intersection centroid. This likely explains the finding that six locations were reported twice, each on different dates. However, the subsequent processing that was applied to the case location data, and the control location selection process, were implemented to minimize systematic differences in how case and control locations were defined. Thus, it is expected that the processing of the location data rendered exposure measurement error to be non-differential, such that any bias would be toward the null. Furthermore, the sensitivity analyses suggest that instances of likely imprecision in the geocoding of the case-locations did not affect the study findings.

The 30 × 30-m scale, MRLC National Land Cover Datasets was the gold standard for measuring tree canopy cover nationally at the time of the analyses, but higher resolution data are becoming available. Thus, these data do not have sufficient resolution to identify individual street trees and their potential impacts on the sidewalk conditions or allow for matching of exposure assessment on day or time (Appendix S1). Furthermore, there may be measurement error in tree canopy cover estimates because the MRLC National Land Cover Data underestimates tree canopy in urban areas.[44] However, the study design individually matches controls to cases on county and population density and adjusts for key measures of urban design. Therefore, we do not have reason to believe that measurement error in tree canopy cover was differential by case-control status and so expect any bias due to exposure measurement error to be toward the null.

Pedestrian volume is a likely predictor of whether a fall will occur at any given location.[30] Our design matched on road type and class and county-specific quintiles of tract-level population density (model 1) and then further adjusted for intersection density, population density, and walkable destinations within 100 m of the locations (model 2), all variables that have been shown to serve as a proxy for pedestrian volume.[25,31,32] Our prior work on pedestrian injuries from automobiles in New York City, where pedestrian count data were available, showed that adjusting for pedestrian count at case and control locations or adjusting for walkability metrics at case and control locations produced very similar results.[27] These prior analyses provide some assurance that adjusting for walkability metrics accounts for confounding by pedestrian volume to a similar extent as controlling for available pedestrian count data. In the current work, a comparison of the results for models 1 and 2 show that further adjustment for these urban design variables modestly diminished case–control associations with tree canopy cover. Further adjustment for measures of area socio-economic conditions (model 3), which are likely to be somewhat associated with pedestrian volume, do not meaningfully alter the OR for tree canopy cover.[44-48] Yet even so, it is possible that these analyses do not fully adjust for pedestrian volume.

Conclusion

This work demonstrates methods to use EMS data to efficiently conduct large scale studies of pedestrian falls. It also suggests that higher tree canopy cover is inversely associated with locations where injurious pedestrian falls occur that EMS responded to. Future research should investigate possible mechanisms for the observed inverse association, especially the temperature lowering effects of tree canopy cover.

Supplementary material

Supplementary material is available at the *American Journal of Epidemiology* online.

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Conflict of interest

The authors declare they have no conflicts of interest related to this work to disclose.

Data availability

The data underlying this article were provided to Columbia University researchers under a Data Use Agreement by ESO Solutions, LLC and so cannot be shared directly. Researchers wishing to access EMS data should contact ESO Solutions.

Disclaimer

The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health nor the USDA.

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