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Multiscale Analysis of Pedestrian Crossing Distance

Marcel E. Moran[a] and Debra F. Laefer[a,b]

[a]Center for Urban Science and Progress, Tandon School of Engineering, New York University, Brooklyn, NY, USA; [b]Department of Civil and Urban Engineering, Tandon School of Engineering, New York University, Brooklyn, NY, USA

ABSTRACT

Problem, research strategy, and findings: Crossing distance is considered a factor in both pedestrian safety and behavior. However, it has seldom been quantified within or across entire cities or related to walking outcomes. Combining data encoded in OpenStreetMap and drawn from high-resolution satellite imagery, we measured formal pedestrian crossings throughout a dense European city (Paris [France]), a dense American city (San Francisco [CA]), and a less-dense, more car-centric American city (Irvine [CA]). This granular approach—covering roughly 49,000 total crossings—identified inter- and intraurban spatial patterns in the distribution of pedestrian crossing distance, including clusters of long crossings that likely deter walking and increase its risk. By overlaying recent pedestrian–vehicle collisions on these novel data sets we found that longer crossing distance correlated with increased likelihood of collisions, raising the salience of traffic-calming interventions.
Takeaway for practice: Quantifying pedestrian crossing distance at the scale of entire municipalities empowers transportation planners to identify pedestrian-hostile crossings (individuals and clusters), add context to collision trends, and geographically target locations for traffic calming. These cases collectively demonstrate how the increasing prioritization of the automobile in city planning quantitatively changes (and degrades) the pedestrian environment, as well as how low-tech investments, such as sidewalk extensions and refuge islands, can mitigate these trends.

KEYWORDS
Crosswalks; GIS; pedestrians; safety; satellite

Pedestrians face the greatest risk of automobile collisions when crossing a street: the longer a crossing, the higher their exposure is to oncoming cars. Despite the relevance of crossing distance, few studies have considered its variance within or across entire cities. Given that, we probed pedestrian crossing distance at the municipal scale, leveraging both OpenStreetMap and satellite imagery to quantify crossing distances at roughly 49,000 formal crossings (those parts of the roadway designated for pedestrians to cross), both marked and unmarked, at intersections and at midblock. The methodological approach developed here can aid planners and researchers in identifying intra-city spatial patterns in crossing distance and, consequently, siting traffic-calming measures to improve safety and increase walkability. By selecting three markedly different cities as case studies (Paris [France], San Francisco [CA], and Irvine [CA]; see Figure 1), this can also illustrate how varying planning paradigms, and the increasing prioritization of automobiles, generate unique distributions in crossing distance throughout pedestrian networks. In addition, these novel data sets can add context to pedestrian–vehicle collisions by spatially linking collision locations to the crossings where they occur and performing regression analyses of crossing distance with the probability that a pedestrian–vehicle collision has occurred.

The growth of pedestrian fatalities in the United States, which have increased since 2011 following decades of declines (Kim, 2023; Schneider, 2020), necessitates renewed attention from transportation planners and researchers. Several factors have been implicated in this distressing trend, including increased driving, popularity of sport utility vehicles and light trucks over sedans, suburbanization of lower-income households, and drivers distracted by smartphones (Sanchez Rodriguez & Ferenchak, 2023;

CONTACT Marcel E. Moran marcel.moran@nyu.edu

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Figure 1. Pedestrian crossing in Paris (France; left) and Irvine (CA; right). Photos by the author (left) and Google Maps Street View (right).

Schmitt, 2020; Tyndall, 2024). In contrast, pedestrian fatalities in Europe decreased by 20% between 2010 and 2018 (Nuyttens, 2020), with a similar decline in the prior decade (Pace et al., 2012), indicating the opportunity to learn from this success. In addition, the increasing share of older adults in both American and European cities further heightens the risk of pedestrian–vehicle collisions (Hong, 2023; Mather & Scommegna, 2024; Rasmussen et al., 2020).

We proceed here with a literature review of academic studies on pedestrian crossing distance, including limited attempts at quantifying its influence on traffic safety. This is followed by a methods section detailing the usage of the python package OSMnx, as well as high-resolution satellite imagery, to measure pedestrian crossing distances throughout Paris, San Francisco, and Irvine. The results visualize how crossing distance varied both within and across entire cities, with unique spatial patterns, as well as how in each case study crossing distance correlated with increased probability of pedestrian–vehicle collisions. In the discussion we consider how urban analytics of this kind can aid transportation planners in probing their pedestrian networks and geographically target street upgrades to shorten pedestrian crossings. We close by suggesting future research directions built on these analyses, including greater personalization in trip planning applications and inputting crossing distance into pedestrian behavior models.

Background

Research on Pedestrian Crossing Distance

Urban pedestrian crossings vary in a number of ways, including whether they occur at road intersections (Knoblauch et al., 2001), the presence or absence of marked crosswalks (Moran, 2022b), vehicular speed limits (Fridman et al., 2020), the ubiquity of traffic lights and pedestrian signals (Gårder, 1989), and traffic-calming street designs, such as intersection daylighting and chicanes (G. Lee et al., 2013). However, a fundamental attribute of all crossings is their length: the distance a pedestrian must travel across an active roadway. As this distance increases, so does a pedestrian's exposure to automobile traffic. For this reason, street design guidelines emphasize reducing crossing distance via a number of approaches (Duncan et al., 2016), such as by splitting a crossing into sections via pedestrian refuge islands or shortening a crossing by extending adjacent sidewalks (Feuer et al., 2020).

Despite the fundamental importance of pedestrian crossing distance, there have been few studies of the topic, especially those that focus on scales broader than individual intersections or corridors. The largest such analysis included roughly 1,600 signalized intersections in Utah between 2010 and 2019, finding a positive correlation between collisions and crossing distance: a 5% increase in collisions for every 12 additional feet of crossing distance (Islam et al., 2022). In Oregon, Monsere and colleagues (2016) reviewed a range of crossing types and collisions between 2007 and 2014, calculating risk ratios above 1 for both four- and five-lane roads (but not one-, two-, or three-lane roads), indicating a positive association with the longest crossings. Though numerous studies have investigated how crossing characteristics affect pedestrian and motorist behavior, such as signal timing and intersection design (Lipovac et al., 2013; Ridel et al., 2018; Zhang et al., 2019), crossing distance has largely been omitted.

Applications of OpenStreetMap, OSMnx, and Satellite Imagery

Launched in 2004, OpenStreetMap is a world map built on data submitted by a large community of volunteers (Coast, 2015; Minghini et al., 2019), who number in the hundreds of thousands (Budhathoki & Haythornthwaite, 2013). OpenStreetMap's underlying data are available via an open license, which has made it attractive for a wide range of urban research, including in the context of transportation planning (Mooney & Minghini, 2017). For example, Bartzokas-Tsiompras (2022) calculated total pedestrian sidewalk lengths for 992 cities, finding marked differences between more dense, walkable European cities and those in all other regions.

In 2017, Boeing introduced OSMnx, a python package that allows users to extract, visualize, and analyze street network and other geospatial information from OpenStreetMap. This package has enabled scholars to relate cycling behavior to street network characteristics (Alattar et al., 2021), input data from OpenStreetMap into transportation microsimulations (Dingil et al., 2018), and evaluate how street networks can better support active travel (Yen et al., 2021). OSMnx allowed us to extract and analyze pedestrian crossings encoded in OpenStreetMap for the case study cities.

In addition to data drawn from OpenStreetMap, we measured pedestrian crossing distance via review of satellite imagery. Google's mapping platforms, including Google Earth and Google Earth Engine, allow users to view satellite imagery of urban areas and to perform spatial analyses (Gorelick et al., 2017; Yu & Gong, 2012). The increased availability and resolution of satellite imagery on these platforms and others has led to numerous urban research applications, such as measuring the fringes of sprawl (Bhatta et al., 2010) and relating impervious surfaces to heat islands (Imhoff et al., 2010). In the context of transportation planning, satellite imagery has been used to estimate traffic volumes (McCord et al., 2003), map the distribution of on-street parking (Moran, 2020), and predict road quality (Brewer et al., 2021).

Quantifying Crossing Distance Using OpenStreetMap and Satellite Imagery

Our study's primary aim was to measure the distance of formal pedestrian crossings throughout the case study cities as comprehensively as possible. We included formal crossings at both intersections and midblock, as well as those with and without *marked* pedestrian crosswalks, because many formal crossings are unmarked. This entailed treating any formal crossing between a sidewalk and refuge island, or connecting two refuge islands, as distinct. Thus, if an intersection included a refuge island, both crossings leading to it were measured separately, rather than calculated as a merged, longer crossing (see Figure 2). City selection was guided by choosing municipalities that ranged in density, built forms, and transportation patterns (see Table 1).

Using the python package OSMnx, we generated a spatial data layer of all *ways* (connected nodes) that represented pedestrian crossings in OpenStreetMap for each city (see Figure 3). Importantly, these layers varied in both accuracy and completeness of the pedestrian crossings they represent because of the crowdsourced nature of OpenStreetMap's data. First, the accuracy of each pedestrian crossing encoded in OpenStreetMap is contributor dependent. For example, some crossings in OpenStreetMap extended into the sidewalk itself (exaggerating their length), whereas others failed to fully cover the span from sidewalk to sidewalk.

To reduce these potential measurement errors, we next overlaid the crossing distances generated from OSMnx as lines on top of satellite imagery

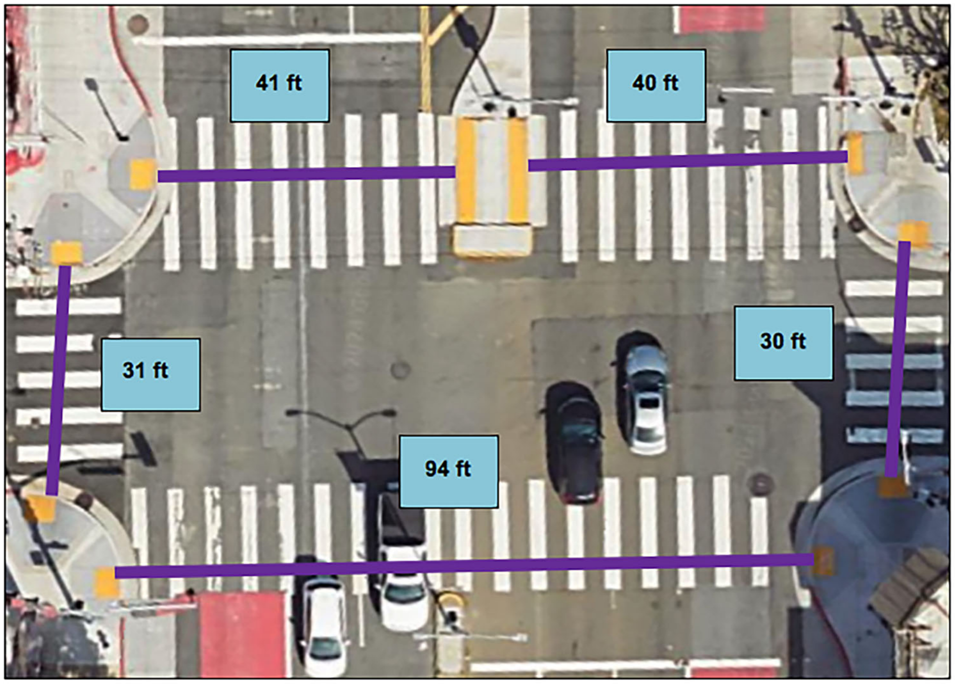

Figure 2. Pedestrian crossings at a San Francisco intersection labeled using satellite imagery drawn from Google Earth. Crossings between sidewalks and pedestrian refuge islands are treated as distinct.

Table 1. Characteristics of pedestrian crossing distance case studies.

	Paris (France)	San Francisco (CA)	Irvine (CA)
Spatial extent (mi^2)	41.00	46.90	65.92
Population	2,119,682	807,774	313,705
Population density (people per sq. mile)	51,700	17,223	4,759
Commute mode share, walking (%)	16	9	3
Commute mode share, driving alone (%)	43	29	59

Notes: French walking and driving figures are drawn from Nienhaus et al. (2023) and reflect modal share of all trips rather than just commutes. U.S. figures are drawn from the American Community Survey (U.S. Census Bureau, 2023, 1-year estimates).

within Google Earth, which allowed for a manual spot-check for accuracy. Though time-consuming, this step ensured that crossing distances incorporated refuge islands (meaning they were treated as two separate crossings) and did not extend into sidewalks themselves. We note opportunities to avoid this manual step in future applications of this methodology in the closing discussion.

With the OSMnx-generated crossing distances now standardized, the next step was to ensure crossings omitted entirely in this data layer were added. This was necessary given that OpenStreetMap did not, at the time of our study, include all pedestrian crossings for the cities we analyzed. Missing crossings were measured via Google Earth's measurement tool, wherein each new line drawn between two sidewalks *not covered* by the OSMnx output generated a new record in the spatial database holding all crossing distances. This process entailed starting each crossing measurement directly where the sidewalk met the roadway pavement at intersection and midblock crossings and concluding at the next-adjacent refuge island or sidewalk via a straight line (see Figure 2). The completion of this step resulted in a spatial layer that included formal pedestrian crossings throughout each case study as comprehensibly as possible given existing OpenStreetMap coverage and satellite imagery.

With these spatial data sets for each city now generated, this created the opportunity for various analyses, including relating pedestrian crossing distance to traffic safety outcomes. We obtained pedestrian–vehicle collision data from municipal open data portals for Paris and San Francisco, respectively, and the University of California, Berkeley, Transportation Injury Mapping System for Irvine. All three of these collision data sets rely on police

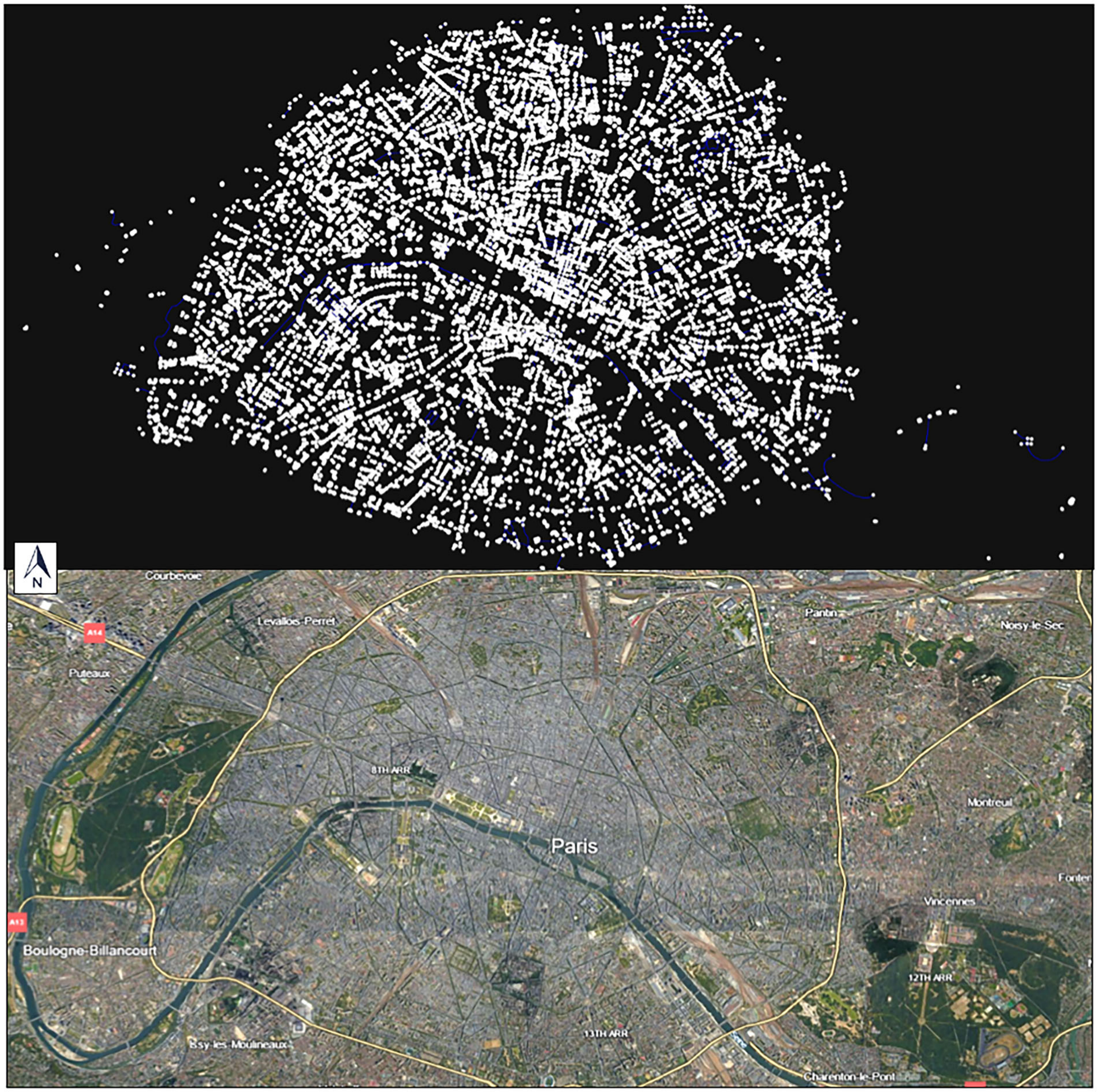

Figure 3. Graph of pedestrian crossing ways (connected nodes) in Paris, generated by the Python package OSMnx (top). Satellite imagery of Paris, drawn from Google Earth (bottom).

reports taken in person, which can suffer from underreporting biases and accuracy issues (Teanby, 1992). To account for changes in these crossings over time, we analyzed only the three most recently available years of pedestrian–vehicle collisions for each city (2021–2023 for San Francisco and Irvine, 2020–2022 for Paris). Those collisions (as point data) were overlaid on the newly generated pedestrian crossing distance layers, wherein each collision was spatially joined with the crossing where it occurred. Given the primacy of formal pedestrian crossings in this study, we excluded collisions that occurred outside of crossings (meaning elsewhere on the roadway).

Pedestrian Crossing Distance Varies Sharply Within and Across Cities

By combining data extracted from OpenStreetMap with satellite imagery, we were able to quantify the distance of roughly 49,000 formal pedestrian crossings in Paris, San Francisco, and Irvine, finding both intra- and intercity spatial patterns and distinct numerical distributions. Average pedestrian crossing distance was shortest in Paris (26 ft, $SD = 11$), followed by San Francisco (43 ft, $SD = 14$) and Irvine (58 ft, $SD = 23$). Mapping these data sets visualized the complex ways pedestrian crossing distance varied across space (see Figure 4 and

Figure 4. (a) Pedestrian crossing distance in Paris. This view excludes crossings in two large parks on Paris's eastern and western end, Bois de Vincennes and Bois de Boulogne. (b) Pedestrian crossing distance in San Francisco. This view excludes crossings on Treasure Island. (c) Pedestrian crossing distance in Irvine. Crossings within identified gated communities have been excluded.

Supplemental Appendix for equivalent figures in grayscale).

Visually, the most striking effect of these data sets was that crossing distance did not vary randomly across these cities but instead exhibited unique, city-specific patterns. This was particularly true in the context of corridors that stood out as linear strings of long crossings. To better visualize such corridors, Figure 5a features all but those that are 70 ft and above, revealing marked intercity differences. First, Paris had very few such crossings (just 0.3% of its total), and those that did exist were broadly clustered in the city's western half, many of which did not directly neighbor others. In comparison, San Francisco had a higher number and share of crossings 70 ft or longer (roughly 4.4% of its total), which primarily laid along specific corridors across the city. In Irvine, long crossings were common (20% of total) and appeared throughout the city. Indeed, they approximated the outline and main roads of the entire city, signaling a grid of wide arterials built around car travel. There were also meaningful intercity comparisons for short crossings (see Figure 5b); a much higher share of crossings in Paris were 15 ft or less (11%), compared with just 1% in San Francisco and less than 1% in Irvine. Such short crossings were distributed throughout Paris, though in San Francisco, they were present in only a few clusters, and they were very rare in Irvine.

Histograms for each city illustrate how pedestrian crossing distances approximated Gaussian distributions in Paris and San Francisco: they were less common at very high and very low distances and

Figure 5. Paris, San Francisco, and Irvine pedestrian crossings 70 ft and longer (left) and Paris, San Francisco, and Irvine, pedestrian crossings 15 ft and shorter (right). Maps are set to different scales.

crested around a mean value (see Figure 6). However, each case maintained idiosyncratic components; in Paris, the Haussmannian grid established in the late 19th century included a massive number of narrow streets (and crossings) bisected by a smaller number of wider boulevards (Jordan, 1995). The sharp spike at roughly 40 ft in San Francisco's histogram likely reflects the uniform nature of many of its western neighborhoods, which follow a strict, rectangular grid established in the late 1860s

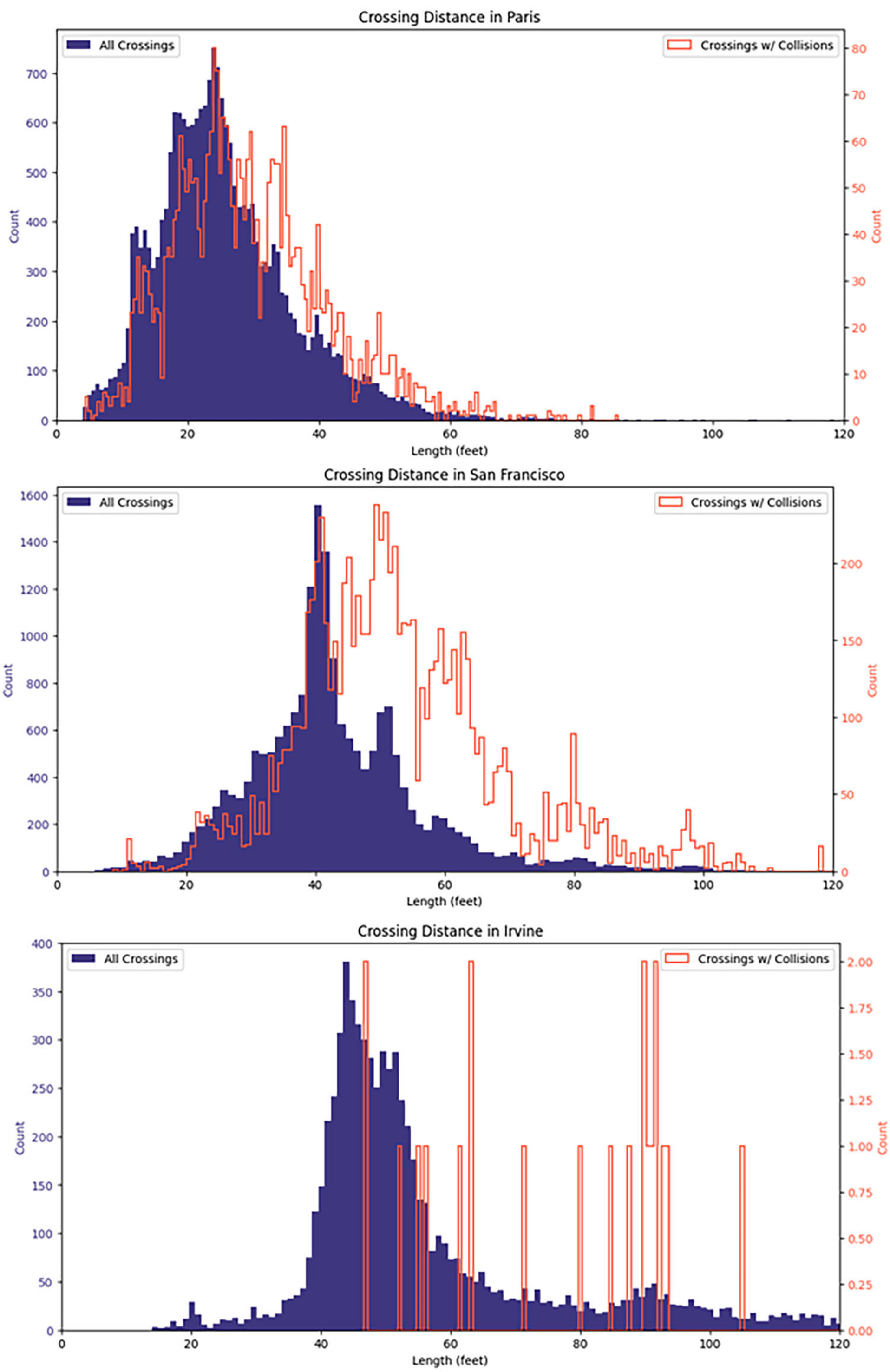

Figure 6. Histograms of pedestrian crossing distance for all crossings (shaded) and crossings where collisions recently occurred (white).

(Ungaretti, 2005). Irvine's histogram included a second, smaller crest of crossings greater than 80 ft, which represented lengthy crossings along the grid of wide, car-centric streets that were distributed across the city, pointing to its significant postwar development (Forsyth, 2005).

In each city, crossings where recent collisions occurred were longer, on average, than crossings overall. This ranged from a 15% increase in Paris to a 23% increase in San Francisco and to a 43% increase in Irvine (see Figure 7a). These averages do not directly compare the relative safety of streets in

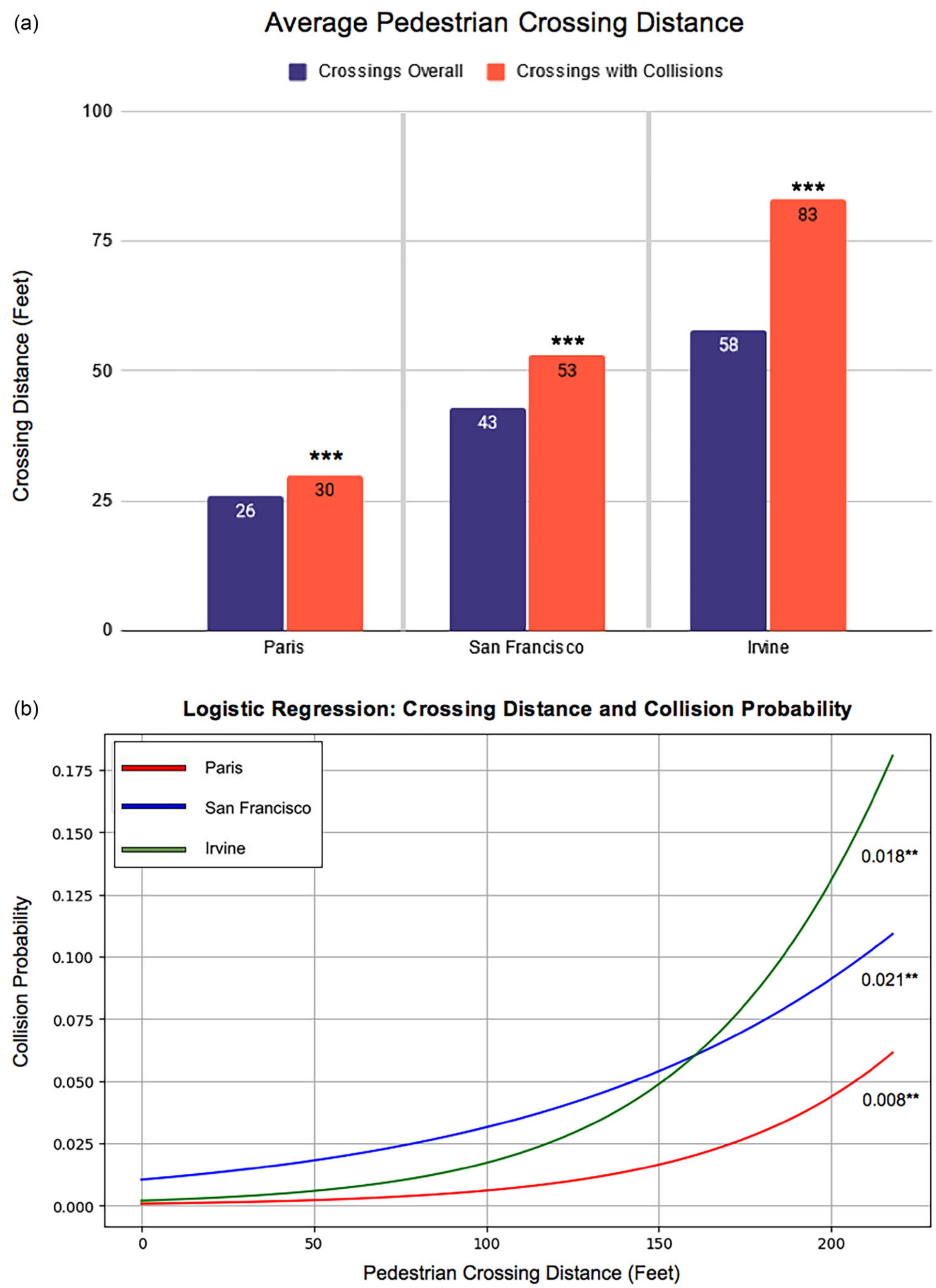

Figure 7. (a) Bar graph comparing average pedestrian crossing distance for all crossings (dark), versus those where collisions occurred (light). ***Statistically significant difference in these averages ($p < .01$). (b) Logistic regression curves indicating the change in probability of a collision as pedestrian crossing distance increases. **Statistically significant coefficients ($p < .05$).

each city (which requires data on vehicle and pedestrian volumes, among others) but how crossing distance within each city related to collisions locally. *T*-tests indicated that the differences between the average distance of all crossings and crossings where collisions occurred was statistically significant in each city ($p < .01$). In addition, logistic regression demonstrated that in each city, as the length of a pedestrian crossing increased, the probability that a collision has occurred also increased, with statistically significant correlation coefficients ($p < .05$; see Figure 7b). Specifically, for every 1-ft increase in crossing distance, the probability that a collision has occurred increased by 0.8% in Paris, 2.11% in San Francisco, and 1.8% in Irvine. As the slopes of the logistical regressions highlight, the relationship between crossing distance and probability of a collision was not uniform; instead, in all three cities, each additional foot of crossing increased the probability of a collision to a greater

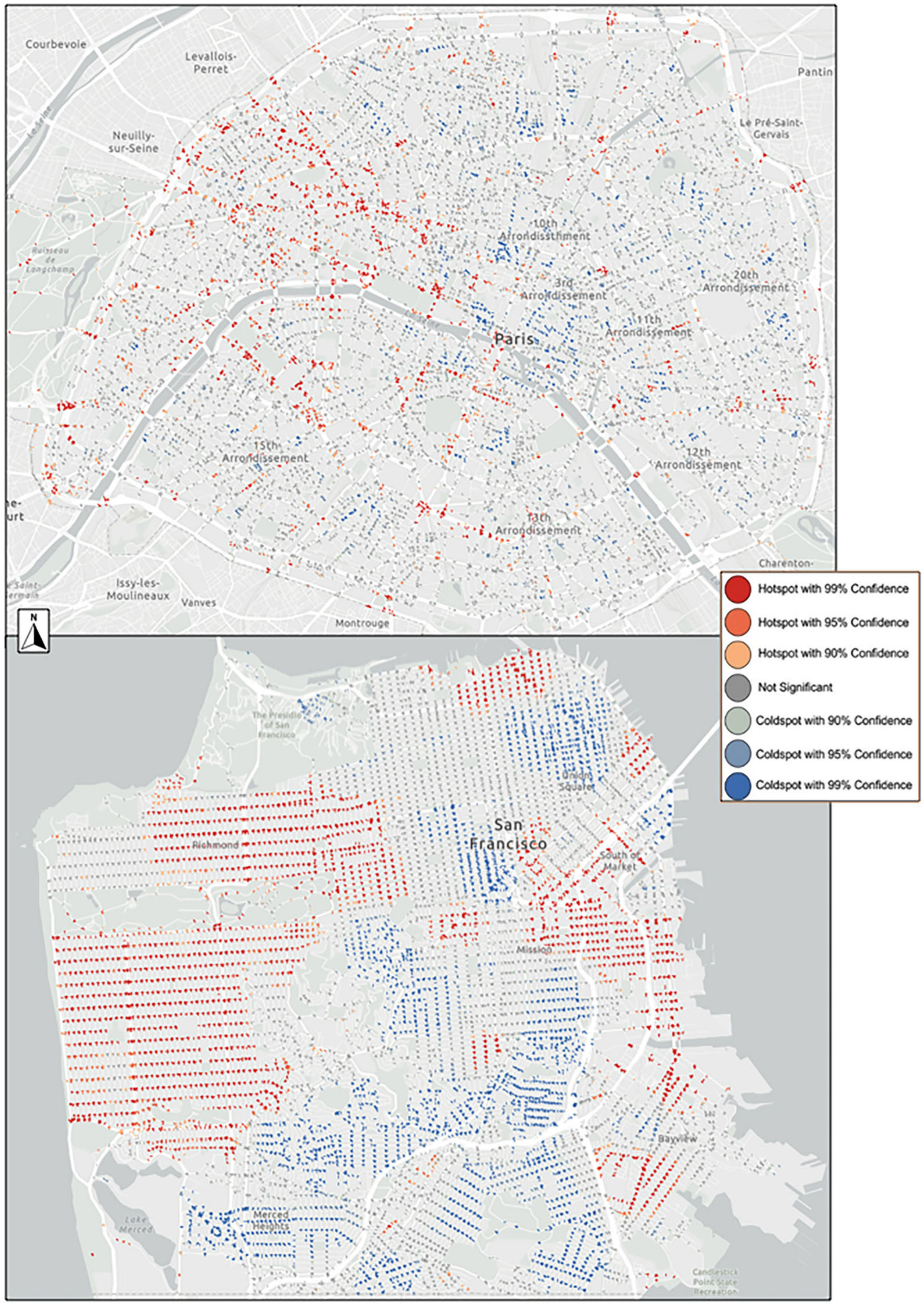

Figure 8. Hotspot analysis of pedestrian crossing distance in (top) Paris and (bottom) San Francisco. Areas of darkest hues represent clusters of longer or shorter crossings. Maps are set to different scales.

extent. Put another way, the collision probability increase when a crossing distance was extended from 60 ft to 61 ft was greater than the collision probability increase when a crossing distance was extended from 9 ft to 10 ft in all three cities.

Hotspot analyses (Getis-Ord Gi*; Getis & Ord, 1992) provided additional insight into how pedestrian crossings clustered by distance (see Figure 8). This method detects crossing distance *hotspots* (where longer crossings neighbor each other) as well as crossing distance *coldspots* (where shorter crossings neighbor each other). Rather than highlight individual long crossings or corridors of long crossings, this approach instead identifies broader patterns in crossing distance, such as how they overlap with or diverge from neighborhood boundaries. In Paris, long-crossing hotspots were mostly present in its western half and clustered around some of the city's monuments and tourist sites (such as the Eiffel Tower, Jardin Tuileries, and Champs Élysées), whereas its coldspots were more evenly distributed, indicating many highly walkable areas. In San Francisco, almost all the city's western neighborhoods comprised a single long-crossing hotspot, though they were not exclusively confined to that area of the city. For Irvine, hotspot analysis revealed a different pattern entirely (see the Supplemental Appendix), in which long-crossing hotspots were primarily single intersections where each crossing approached or exceeded 100 ft and formed a grid of wide roads that surrounded residential areas in which shorter crossings appeared. Hotspots and coldspots in crossing distance were calculated relative to each city and were not directly comparable case to case.

Summary of Quantitative Findings

Measuring pedestrian crossing distance within three municipalities allowed us to identify intra- and intercity spatial variance of this fundamental street attribute at new scales. Using a combination of data encoded within OpenStreetMap and measured from satellite imagery, we quantified the distance of roughly 49,000 formal crossings within Paris, San Francisco, and Irvine, finding unique numerical and spatial distributions, including large differences in the percentage and arrangement of long crossings, which are both more dangerous for and less inviting to pedestrians. Overlaying recent pedestrian–vehicle collisions on these newly generated crossing distances determined that in all three cities, crossing distance was positively correlated with the probability that a collision recently occurred. Logistic regressions specifically pointed to the danger of long crossings, for which each additional foot of distance raised the probability of a crash to a greater extent.

For the three cities in which pedestrian crossing distances were fully measured, Paris had the shortest average crossing distance (26 ft) and the lowest percentage of crossings of 70 ft or longer (0.3%). This was due to a combination of Paris's narrow streets and its robust investment in curb extensions and refuge islands (Herrada, 2023). In comparison, Irvine's average pedestrian crossing distance was more than twice as long (58 ft), and approximately one-fifth of its total crossings were 70 ft or longer. This captured the prominence of wide streets and the prioritization of automobile throughput common to many American municipalities, likely deterring walking and endangering those who do so. San Francisco fell in the middle of these three cases, with an average pedestrian crossing distance of 43 ft and 4.4% of its crossings at 70 ft or more. Like Paris, San Francisco has also decreased crossing distances via traffic-calming investments (Brill et al., 2013), though some corridors of long crossings remained.

Implications for Planning Practice and Future Research Directions

Quantifying and visualizing pedestrian crossing distance at the scale of entire municipalities has a number of implications for transportation planning. First, this approach pinpoints a city's longest crossings, which can help planners prioritize shortening them to improve safety outcomes, including via modular interventions such as refuge islands and sidewalk extensions. Indeed, comparing the distance of all crossings versus those where collisions occurred demonstrates the relative paucity of collisions at shorter crossings, from which planners can perhaps identify a locally relevant target distance to bring as many crossings in line with as possible.

Second, beyond simply which specific crossings are the longest, these methods identify clusters of crossings of similar distances, creating a more nuanced understanding of a city's pedestrian environment and where to intervene. Identifying crossing distance hotspots moves beyond individual intersections or corridors to consider long-crossing *neighborhoods* that could be addressed collectively. This also points to how patterns in crossing distance over a broader area (such as along the path to school or work) may exert influence on walking behavior more so than do individual intersections.

A fundamental limitation of this study was the challenge of mapping pedestrian crossings throughout entire cities. First, OpenStreetMap varies in terms of its completeness in capturing this attribute, a variation inherent to volunteered geographic information, as has been noted by other analyses of such underlying data (Biljecki et al., 2023; Mooney & Minghini, 2017). When supplementing OpenStreetMap crossings with satellite imagery, other problems remained, such as false positives (when a crossing was mapped that no longer existed) and true negatives (when a crossing that existed was not mapped). Both of these can occur due to the crossing in question being obscured by tree cover, building shade, or construction materials. Together, this means the results presented here are the best attempt at mapping every pedestrian crossing in these cities, though given the size of the data sets, there is undoubtedly data underreporting (as well as incorrectly inputted records), which likely comprise a very small percentage overall. Further, the methodological approach taken here omitted *informal* crossings, which may in some cities capture a meaningful portion of pedestrian traffic. In the specific case of Irvine, an added challenge was the presence of gated communities that maintain their own streets (and thus crossings), which are not public property. We attempted to exclude crossings that were within gated communities.

Our use of pedestrian–vehicle collision data also brought limitations due to known errors in collision reporting, such as underreporting generally (Doggett et al., 2018; Ferenchak & Osofsky, 2022), and accuracy issues regarding collision location, which are often marked where a victim lands instead of where they were struck by an automobile. Such issues are more common as vehicle speeds and crossing distances increase and if the victim was unconscious or killed and thus unable to correct the record. This likely means an undercounting of pedestrian–vehicle collisions, particularly at longer crossings.

In addition, though the pedestrian–vehicle collision data we used in this study covered a 3-year period for each city, crossing distances were calculated at a single time point (drawn from data acquired in 2023), which omitted how they have potentially changed in recent years. Indeed, analyzed collisions occurred in the years immediately following the emergence of COVID-19, during which cities around the world, including Paris and San Francisco, made significant changes to their streets (Kim, 2022; Moran, 2022a). These reallocations of the public right-of-way, many of which benefited pedestrians at the expense of cars (Hake et al., 2023), potentially play a role in the collision data, as did changes in driver behavior in the wake of the pandemic, such as increased speeding (Wang & Cicchino, 2023).

There are a number of directions future research on this topic can take. First, further automating the methods we employed here can accelerate quantifying pedestrian crossing distance for many more cities around the world. This can occur in two concrete ways: First, the scripts used to download crossings from OSMnx can be refined to better incorporate the presence of refuge islands, which would markedly reduce the need to subsequently review and modify those outputs. Second, the manual review of satellite imagery to identify crossings not currently present in OpenStreetMap we undertook for this study could be used as training data for automating the detection of crossings elsewhere, as research teams have pursued for other street features (Verma & Ukkusuri, 2023). Indeed, the methodology we have established in this study does not represent the end of a process but instead the first attempt at leveraging data sources for crossing distance at new scales that can be expanded on and improved iteratively.

Aside from refining the data collection, these findings point to future analytical opportunities. Indeed, generating similar data sets for a larger number of cities could test whether and to what extent correlations between crossing distance and collisions hold more broadly. Within cities, there is also now the chance to consider how crossing distance relates to a range of socioeconomic, built environment, and transportation variables, such as racial diversity, income, land use, and vehicle ownership. Moreover, rather than at a single moment in time, measuring crossing distance longitudinally could also be fruitful, creating the chance to track coinciding changes in collisions as well as the potentially protective effect of traffic-calming investments.

Relatedly, passively collected data from mobile devices could be mined to understand whether and how crossing distance correlates with aggregate pedestrian behavior, building on similar inquiries (K. Lee & Sener, 2017). Indeed, these data could augment existing evidence that longer pedestrian crossings may deter walking generally, and particularly among certain groups, including older adults, parents with strollers or young children, and persons with mobility impairments (Levi et al., 2013; Pecchini & Giuliani, 2015). For instance, how much longer an overall route might a pedestrian choose to avoid individual or multiple long crossings? Passively collected data could also provide a measure of pedestrian volumes to statistically control associations between crossing distance and collisions. The increase in sophistication of pedestrian models, such as those that now incorporate different measures of trip impedance beyond simply trip distance (Sevtsuk et al., 2024), could potentially benefit from including crossing distance at this fine-grained scale. Finally, quantifying pedestrian crossing distance across cities could also augment trip planning applications, especially for pedestrians who wish to avoid long crossings, following a larger trend in wayfinding personalization (Novack et al., 2018; Park et al., 2021).

In closing, we deployed data from OpenStreetMap and satellite imagery in a novel way to quantify pedestrian crossing distance throughout multiple cities. This approach allowed for comparisons within and across these cases, identification of unique spatial patterns, and illustration of how crossing distance related to recent pedestrian–vehicle collisions. This advances the study of pedestrian infrastructure to a both a finer grain and larger scale, with transferable methods and applications for urban researchers, transportation planners, and pedestrian safety advocates.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

Notes on Contributors

Marcel E. Moran marcel.moran@nyu.edu
Debra F. Laefer debra.laefer@nyu.edu

ORCID

Marcel E. Moran http://orcid.org/0000-0002-5637-4971
Debra F. Laefer http://orcid.org/0000-0001-5134-5322

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