

Walkable on paper, walkable on the street? Divergence between Walk Score and streetscape quality in Los Angeles

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Abstract

Walk Score is widely used as a proxy for neighborhood walkability and for assessing environmental equity, yet it has been validated mainly against destination accessibility rather than the streetscape pedestrians actually see. Using 2,232 census block groups in the City of Los Angeles, this study links 2018 Walk Scores to eye-level streetscape measures derived from 2022 Google Street View imagery through semantic segmentation and zero-shot vision–language model ratings, and estimates spatial error models for both the Walk Score and a signed divergence index. Walk Score correlated negatively with a composite pedestrian streetscape quality index ($r = -0.36$), and 61.3% of block groups were discordant across the two measures. Conditional associations varied by attribute: sidewalk view and the VLM-rated well-maintained and interesting scores were positively associated with Walk Score, whereas the pleasant/inviting versus car-dominated score was negatively associated. Divergence was systematic rather than random. Block groups scoring high on paper but low on the street had a mean block-group median household income of \$57,700, compared with \$124,500 where the pattern reversed, and lower income and owner-occupancy remained significant predictors of divergence after accounting for spatial dependence. Accessibility-based walkability indices can therefore understate streetscape disadvantage precisely in the neighborhoods where that disadvantage is concentrated.

1. Introduction

Walkable environments have been treated as important neighborhood characteristics in research on urban planning, transport, health, and spatial equity. Among the various measures used to assess them, the Walk Score has been used as an indicator of neighborhood walking environments because it facilitates comparisons across areas (Carr et al., 2010; Duncan et al., 2011; Hall & Ram, 2018). The Walk Score ranges from 0 to 100 and incorporates distances to everyday destinations and street-network characteristics such as block length and intersection density. Previous studies have found associations between Walk Scores and GIS-based walking environment indicators, including destination density, residential density, and intersection density (Carr et al., 2010; Duncan et al., 2011). However, this index was not designed to directly measure microscale streetscape conditions experienced by pedestrians, such as sidewalk conditions, greenery, vehicle exposure, aesthetics, and maintenance. Therefore, a high Walk Score can be interpreted as an advantage in destination accessibility, but it cannot readily indicate the quality of the eye-level streetscape to the same extent. This distinction in measurement scope needs to be considered when using the Walk Score to assess environmental equity across neighborhoods (Conderino et al., 2021).

Research on walking environments has measured the characteristics at different spatial scales. At the neighborhood scale, it initially focused on urban form, including density, land-use diversity, and street-network design, and subsequently expanded to include destination and public transport accessibility (Cervero & Kockelman, 1997; Ewing & Cervero, 2010). At the pedestrian scale, the focus is on the characteristics observed at eye level on actual streets, including sidewalks, greenery, visual enclosure and visual complexity (Ewing & Handy, 2009). Field audit tools have also been developed to measure

microscale characteristics systematically (Day et al., 2006; Millstein et al., 2013). Studies have reported relationships between microscale streetscape conditions and walking behavior (Boarnet et al., 2011; Cain et al., 2014), whereas studies examining variables at multiple spatial scales have suggested that street-level measures can provide information beyond neighborhood-level indicators (Koo et al., 2022). Thus, the two scales of the environment must be understood as related but distinct objects of measurement (Forsyth, 2015).

Eye-level streetscape conditions have primarily been measured through field observations. However, surveying large urban areas is constrained by time and cost (Day et al., 2006; Millstein et al., 2013). Street-view imagery, such as Google Street View (GSV), has been used to observe streetscapes without visiting sites in person (Rundle et al., 2011; Biljecki & Ito, 2021). Advances in computer vision have enabled the measurement of the proportion of greenery visible in images (Li et al., 2015), visual enclosure based on the composition of buildings and the sky (Yin & Wang, 2016), and streetscape components such as sidewalks and roads through semantic segmentation (Nagata et al., 2020). More recently, approaches using pretrained vision-language models (VLMs) and multimodal models have been proposed to assess the relationships between images and natural-language descriptions (Huang et al., 2024; Lin et al., 2025). These methods provide a basis for measuring and comparing neighborhood walking environments and eye-level streetscape conditions across the same urban area.

Differences in walking environments measured using different scales have also been reported in previous studies. Some socioeconomically disadvantaged areas have shown relative advantages in macroscale walkability indicators because of their high density and destination accessibility, a pattern discussed as the disadvantaged advantage (King & Clarke, 2015). A study of 500 US cities also found that low-income areas had higher Walk Scores than high-income areas (Conderino et al., 2021). In contrast, studies directly assessing microscale environments have found relatively unfavorable conditions in some characteristics, such as aesthetics and maintenance, in low-income and racial minority neighborhoods (Thornton et al., 2016; Zhou et al., 2019). Similarly, research in Los Angeles suggested that assessments of macroscale walking environments and street-view-based microscale environments differ and that these differences may be associated with socioeconomic characteristics (Ki & Chen, 2023). Other studies have proposed walkability indices that combine information at two scales (Ki et al., 2023) or examined the concordance and discordance between physical streetscape conditions and perceptual assessments (Qiu et al., 2023; Song et al., 2025). Building on this work, the conditional relationships between individual eye-level attributes and Walk Score need to be examined alongside the spatial and socioeconomic distribution of the differences between the two measures.

This study examined the relationships and discordance between the Walk Score and eye-level streetscape conditions in Los Angeles. The first research question (RQ1) concerns the extent and direction of the associations between the Walk Score and individual eye-level streetscape attributes after accounting for neighborhood socioeconomic characteristics, urban structure, and GIS-based environmental variables. The second research question (RQ2) concerns the discordance between the two measures and the socioeconomic characteristics associated with their direction and degree. To

address these questions, the two measures were linked to the same census block groups for conditional regression analysis. Concordance and discordance types and a continuous divergence index were constructed to examine the spatial distributions and socioeconomic relationships.

2. Literature review

2.1 Walkability across scales

Walkability is a multidimensional concept that extends beyond individual physical characteristics and encompasses different spatial scales (Forsyth, 2015). At the neighborhood scale, research has focused on measuring land use and urban structure within spatial units to describe the conditions under which walking occurs (Cervero & Kockelman, 1997). At the pedestrian scale, the objects of measurement are the physical, visual, and perceptual characteristics of streetscapes experienced at eye level while walking. These include urban design qualities such as visual enclosure and complexity, as well as elements that pedestrians directly see or use, including sidewalks, street trees, and crosswalks (Ewing & Handy, 2009). Field audit tools such as the Irvine–Minnesota Inventory and the Microscale Audit of Pedestrian Streetscapes have been developed to measure pedestrian-scale characteristics (Day et al., 2006; Millstein et al., 2013). Studies considering environmental factors at both scales have also suggested that street-level indicators provide additional information to explain walking behavior and may capture some neighborhood-level characteristics (Koo et al., 2022). Pedestrian-scale streetscape conditions can therefore be viewed as a measurement dimension that is related to the neighborhood environment but warrants separate consideration in understanding walkability.

Walk Score assesses neighborhood walking environments primarily through destination accessibility and street-network connectivity, and its validation has largely relied on relationships with neighborhood-level urban environmental indicators (Walk Score, 2024). Early studies found significant associations between Walk Score and conventional GIS-based walkability indicators, including destination density, residential density, and intersection density (Carr et al., 2010; Duncan et al., 2011). These indicators relate to the urban environmental characteristics used to assess neighborhood walkability, such as density, land use, and street-network connectivity (Frank et al., 2010). Therefore, the validity of the Walk Score established in previous research needs to be understood mainly within its scope of measuring destination accessibility and neighborhood urban structure, as it does not establish whether the index captures the microscale streetscape conditions that pedestrians directly experience to the same extent. The measurement scope has been discussed previously. Hall and Ram (2018) noted that because the Walk Score is based primarily on destination accessibility and street-network characteristics, it may not adequately reflect the streetscape quality directly experienced by pedestrians, including sidewalks, greenery, aesthetics, and safety. A study comparing the Walk Score with street-view-based microscale walking environments in Los Angeles found different spatial patterns in the two assessments and associations between these differences and socioeconomic characteristics (Ki & Chen, 2023). Research considering both Walk Score and microscale streetscape characteristics also reported that existing indicators alone may not adequately explain pedestrians' subjective assessments and streetscape

quality and proposed a new walkability index to address this limitation (Ki et al., 2023). These findings indicate that Walk Score and pedestrian-scale streetscape conditions do not necessarily yield the same assessment.

Previous studies have compared the differences between the two measurement scales or proposed walkability indices that combine them. In addition, the relationships between the Walk Score and individual eye-level attributes, including sidewalks, greenery, visual enclosure, visual complexity, and vehicle view, need to be examined separately. Whether the direction and significance of these relationships remain after accounting for neighborhood urban structure, such as density, land use, accessibility, and GIS-based environmental variables, is important for interpreting the associations between the two measurement scales. This study treats these conditional relationships as its first analytical focus.

2.2 Measuring eye-level streetscape quality at scale

Street-view imagery has been used to observe the environments pedestrians experience across large areas (Biljecki & Ito, 2021). Early studies proposed methods to measure greenery visible from a pedestrian perspective using the proportion of greenery in images (Li et al., 2015), or to quantify visual enclosure using the visual composition of buildings and the sky (Yin & Wang, 2016). Subsequent applications of computer vision and semantic segmentation have enabled the identification and quantification of streetscape components at the pixel level, including buildings, greenery, sidewalks, roads, and vehicles. Studies have also used these physical components to assess visual walking environments or examine their relationships with walking environment scores (Zhou et al., 2019; Nagata et al., 2020). Street-view imagery has been increasingly used to measure the physical environment at the pedestrian eye level, providing information that is distinct from conventional GIS data.

Measurements using street-view imagery have expanded beyond physical street elements to include the perceptual characteristics of places. Salesses et al. (2013) quantified the perceptions of places, including safety and aesthetics, using multiple comparative assessments of urban images. Subsequent research has combined these assessments with image-based learning to estimate perceptual characteristics across large urban areas (Zhang et al., 2018). More recently, pretrained multimodal models have been used to assess various characteristics of walking environments using images (Lin et al., 2025). However, physical characteristics calculated directly from images and perceptual characteristics assessed by people or models do not always exhibit the same spatial patterns. Studies comparing objectively measured streetscape conditions with perceptual assessments reported different patterns of concordance and discordance (Qiu et al., 2023; Song et al., 2025). This suggests that eye-level streetscape quality may also contain different information, depending on the measurement approach.

The quality and spatial and temporal coverage of imagery must be considered when using street-view imagery for large-scale analyses. In addition to individual image characteristics, such as blur, occlusion, and lighting, differences in spatial coverage and capture dates can affect the measurement of

streetscape conditions within the same area (Hou & Biljecki, 2022). Variations in street-view availability and image capture dates across areas have also been reported (Kim & Jang, 2023). Therefore, aggregating eye-level indicators at the city scale requires identifying images unsuitable for analysis and examining data characteristics such as image counts and capture dates across areas.

These studies proposed various ways to use street-view imagery to measure physical and perceptual streetscape conditions across cities. Some have used these measures to construct new walkability indices or compare the concordance and discordance across measurement approaches, while relationships between objective and perceptual streetscape conditions have also received increasing attention (Qiu et al., 2023; Song et al., 2025). In addition, the extent and direction of the alignment between a widely used neighborhood-level walkability indicator and eye-level streetscape measures within the same location warrant examination. Examining the relationships between individual eye-level attributes and existing neighborhood-level walkability indicators may help distinguish environmental characteristics captured at different measurement scales.

2.3 Scale, inequality, and the research gap

Equity studies using macroscale walkability indicators have reported that socioeconomically disadvantaged areas do not necessarily exhibit poor walkability. Using national U.S. data, King and Clarke (2015) found relatively high walkability in some socioeconomically disadvantaged areas. Conderino et al. (2021) examined 500 US cities and found that low-income areas had higher mean Walk Scores than high-income areas. It has been suggested that this pattern is related to the residential locations of low-income households in high-density areas with good access to public transport and everyday destinations (Ki & Chen, 2023). These studies indicate that socioeconomically disadvantaged areas may have relative advantages in terms of macroscale walkability indicators focused on destination accessibility and density (Talen, 2023).

Studies measuring streetscape conditions at pedestrian eye level have reported different forms of socioeconomic disparities. Research using field audits has found relatively poor conditions in some streetscape characteristics, including aesthetics, maintenance, litter, and graffiti in areas with low income or high racial minority shares (Thornton et al., 2016). Studies on sidewalk conditions and accessibility have identified differences in income, race, and ethnic composition (Rajaei et al., 2021). Research using photographic surveys and street-view imagery has reported differences across areas in the microscale environments directly experienced by pedestrians, including visual enclosure, complexity, maintenance, and greenery (Bereitschaft, 2017a, 2017b; Zhou et al., 2019; Su et al., 2019). These findings suggest that socioeconomic patterns in macroscale accessibility indicators may not always coincide with those in pedestrian-scale streetscapes.

Research directly comparing the two measurement scales has also been conducted. In Los Angeles, Ki and Chen (2023) jointly examined a macroscale walkability index and a microscale streetscape index. They identified areas where high macroscale walkability coexisted with poor microscale walking environments, and suggested that their distribution may be related to socioeconomic characteristics.

Previous studies have primarily focused on comparing group means or identifying particular types of discordance. Further examination is, therefore, warranted to determine the extent to which macroscale advantages and microscale disadvantages occur within the same spatial units and how the entire study area is distributed across combinations of concordance and discordance, including discordance in the opposite direction. Examining this spatial co-occurrence is necessary to connect the socioeconomic patterns in walking environments observed at different measurement scales.

Building on this discussion, this study focuses on three aspects. First, it examines the extent and direction of the associations between Walk Score and individual eye-level streetscape attributes after accounting for neighborhood urban structure, including density, land use, accessibility, and existing GIS-based environmental characteristics. Second, it links the Walk Score and pedestrian-scale streetscape conditions within the same spatial units to construct types that capture concordance and discordance at both high and low levels and examines their spatial distribution. Third, it measures the difference between the two measures using a continuous divergence index and analyzes its relationships with neighborhood socioeconomic characteristics, including income, racial and ethnic composition, and housing tenure, while accounting for spatial dependence. The aim of this study is to examine not only social disparities in walking environments, but also the spatial and socioeconomic structure of differences in assessments across measurement scales.

3. Data and methods

3.1 Study area and data

The study area was the city of Los Angeles, California, USA. Los Angeles contains high-density commercial and business districts and low-rise residential areas with a car-oriented transport environment alongside areas where walking and public transport are concentrated. Socioeconomic characteristics, including income, racial and ethnic composition, and housing tenure also vary across areas, making the city a suitable case study for examining the spatial and socioeconomic structures of walking environments at different scales. Previous research at the block-group level in Los Angeles has reported different patterns of macroscale walking environments and microscale streetscape conditions (Ki & Chen, 2023). This study links the Walk Score and pedestrian eye-level streetscape measures to the same census block groups. For the first research question, the relationships between Walk Score and individual eye-level streetscape attributes were examined after accounting for neighborhood urban structure and GIS-based environmental characteristics, along with models that account for spatial dependence. For the second research question, the types of concordance and discordance between the two measures were identified and a continuous divergence index was used to examine their spatial distribution and socioeconomic characteristics.

The spatial units of analysis were defined using the 2010 census block-group boundaries. Sampling points for GSV image collection were generated in 2,331 of the 2,772 block groups in the City of Los Angeles. Points were allocated with reference to the road length in each block group, with at least three

points in areas containing internal roads distributed as evenly as possible along the road network. Images were captured in four headings at each sampling point. After applying image quality criteria and excluding block groups with unscored Walk Scores or missing socioeconomic data, the final analysis included 2,232 block groups. The 441 block groups without sampling points were mainly located in mountainous areas and some industrial areas, and 99 were excluded based on the quality and missing data criteria (Fig. 1). Socioeconomic variables, including income, were derived from the American Community Survey (ACS) 2013–2017 five-year estimates. GIS data were used to derive urban environmental variables and the 2022 GSV dataset was used to measure eye-level streetscape conditions.

3.2 Variables

The neighborhood-level walking environment indicator was the 2018 Walk Score corresponding to each block group. The Walk Score ranges from 0 to 100 and reflects access to everyday destinations and street-network characteristics, including block length and intersection density (Walk Score, 2024). Values recorded as zero in this dataset were treated as unscored and excluded from the analysis. This treatment was an analytical criterion applied to the dataset. Table 1 presents the definitions and descriptive statistics of the main variables.

Neighborhood-level controls were selected to account for socioeconomic characteristics and urban structures. Socioeconomic variables included median household income, Latino population share, and owner-occupancy rate. The urban structure variables included population density, land-use mix, number of bus stops within $\frac{1}{4}$ mi, and park presence. Income, population density, and bus-stop counts were log-transformed. These variables account for differences in neighborhood population composition, density, land use, and accessibility (Cervero & Kockelman, 1997; Ewing & Cervero, 2010; Frank et al., 2010). GIS-based street-tree counts and sidewalk lengths were added to assess the explanatory contribution of eye-level measures beyond the existing spatial data. The log-transformed rate of violent events per 1,000 residents in 2015–2017 was added to the sensitivity analysis of the Walk Score regression model.

Physical eye-level streetscape attributes were measured by applying semantic segmentation to images in the 2022 GSV dataset. Approximately 3.8% of all images, including blank frames and indoor scenes, were excluded as unsuitable for analysis. This quality-control step addressed the measurement limitations of street-view imagery (Hou & Biljecki, 2022; Kim & Jang, 2023). SegFormer, trained on ADE20K, was used to classify the image components (Zhou et al., 2017; Xie et al., 2021) and to calculate the sidewalk view, green view, vehicle view, visual enclosure, and visual complexity. The three view variables represent the pixel shares of the respective elements. Visual enclosure is the building pixel share divided by the sum of the building and sky pixel shares. Visual complexity represents the entropy of the semantic segmentation categories. These measures are based on previous research on the visual composition of streets and urban design characteristics (Li et al., 2015; Yin & Wang, 2016; Ewing & Handy, 2009). Image-level measures were averaged across the four headings at each sampling point and aggregated at the block group level. The reliability of the aggregate measures is shown in Table S1.

VLM-rated qualities were used as supplementary measures along with physical attributes. A zero-shot approach using CLIP (ViT-B/32) compared the similarity of images to positive and negative prompts, and calculated the softmax score for positive expressions across the two prompt sets (Radford et al., 2021). This approach is related to urban environmental assessments using pretrained multimodal models (Huang et al., 2024; Lin et al., 2025). Of the seven candidate attributes, the green and enclosed attributes were excluded because they overlapped with semantic segmentation measures. The safe and lively attributes were excluded because their relationships with external variables were inconsistent with the named constructs or were weakly associated with the key indicators (Table S2). The retained attributes were pleasant/inviting versus car-dominated, well maintained, and interesting. These scores are hereafter referred to as VLM-rated qualities, to distinguish them from direct human perceptual assessments. Prompt wording sensitivity and scoring procedures are presented in Tables S3a–c and Appendix A.

A pedestrian streetscape quality index (PSQI) was constructed to examine the concordance and discordance between the two measures. $PSQI = [z(\text{sidewalk view}) + z(\text{green view}) - z(\text{vehicle view})] / 3$, the mean of the three standardized components. Here, z denotes standardization using the analytic sample. These components reflect the pedestrian infrastructure, greenery, and visual exposure to vehicles (Millstein et al., 2013; Zhou et al., 2019). The standard deviation of the PSQI itself is not necessarily equal to 1. Four types were defined using the sample medians of the Walk Score and PSQI, 71 and 0.01, respectively: concordant high (A), walkable on paper only (B), walkable on the street only (C), and concordant low (D). These are relative classifications within the sample and do not indicate absolute walking feasibility. This comparison of the concordance and discordance between measures is related to previous streetscape research (Song et al., 2025). Separately from the classification, a divergence index was defined as $D = z(\text{Walk Score}) - z(\text{PSQI})$. Positive values indicate a relatively higher Walk Score than the PSQI within the sample, whereas negative values indicate the reverse. This signed difference is distinct from the absolute magnitude of discordance.

Table 1
Descriptive statistics of the analytic sample

Variable	Mean	SD	Min	Max
Dependent variable				
Walk Score (0–100)	67.7	19.6	1.0	98.0
Macro-level neighbourhood controls (ACS 2013–17; GIS)				
Median household income (log \$)	10.92	0.55	8.64	12.43
Latino residents (%)	47.3	30.1	0.0	100.0
Owner-occupied housing (%)	40.8	27.9	0.0	100.0
Population density (log persons/mi ²)	9.45	0.85	2.28	11.71
Land-use mix (entropy)	0.34	0.14	0.00	0.72
Bus stops within ¼ mile (log)	1.87	0.72	0.00	4.82
Park present (0/1)	0.21	0.41	0.00	1.00
Top-down GIS inventories				
Street trees (count)	16.8	9.8	1.0	81.0
Sidewalk length (GIS, m)	330	223	0	3,380
Eye-level physical attributes (semantic segmentation)				
Visual enclosure (building / building + sky)	0.20	0.10	0.00	0.76
Sidewalk view (share of pixels)	0.04	0.01	0.00	0.13
Green view (share of pixels)	0.17	0.07	0.01	0.49
Visual complexity (class entropy)	0.32	0.01	0.24	0.36
Vehicle view (share of pixels)	0.05	0.02	0.00	0.15
VLM-rated qualities (CLIP zero-shot scores)				
Pleasant/inviting vs car-dominated (CLIP score)	0.52	0.08	0.23	0.78
Well maintained (CLIP score)	0.60	0.09	0.21	0.84
Interesting (CLIP score)	0.14	0.03	0.05	0.28
Derived index				
PSQI (mean of component z-scores)	0.00	0.68	-2.85	2.83

N = 2,232 block groups. Socioeconomic variables: ACS 2013–2017 five-year estimates on 2010 census block-group boundaries. Walk Score: 2018; eye-level measures: 2022 GSV dataset. VLM scores are CLIP

softmax scores for the prompt contrasts in Appendix A. SD = standard deviation.

3.3 Analytical strategy

RQ1 was examined using hierarchical OLS regression models with the Walk Score as the dependent variable. M1 included socioeconomic and urban structure variables and M2 included GIS-based street tree counts and sidewalk length. M3 added five physical eye-level attributes and M4 added three VLM-rated qualities. The changes in explanatory power and joint significance of the additional variable sets were compared across the stages. HC3 robust standard errors were used for OLS to account for heteroskedasticity. Spatial dependence was examined using a row-standardized spatial weight matrix based on queen contiguity of the 2010 block-group boundaries. Moran's I and Lagrange multiplier diagnostics were applied to the OLS residuals (Anselin, 1988; Anselin et al., 1996). A spatial error model (SEM) was then estimated as the main specification, with a spatial lag model (SAR) as a supplementary specification (LeSage & Pace, 2009). PySAL tools were used for spatial analysis (Rey & Anselin, 2007). Unstandardized coefficients and standard errors are reported in the tables, and the coefficients and 95% confidence intervals for eye-level variables are compared graphically.

For RQ2, the indicators and socioeconomic characteristics of the four types were compared, and their spatial distributions were mapped. The OLS and SEM models were then estimated with divergence index D as the dependent variable to examine its relationships with income, population composition, housing tenure, and urban environmental variables. Separately, four sensitivity analyses were conducted for the RQ1 M4 OLS model by adding the violent event rate, or separately restricting the sample to block groups with a population of at least 300, a Walk Score of at least five, or at least five GSV sampling points (Table S4b). The prompt-wording sensitivity analysis for VLM-rated qualities used a separate stratified sample and weighted regression; the model details are presented in Table S3.

4. Results

4.1 Two dimensions of walkability

Across the 2,232 block groups in the final analysis, the Walk Score had a mean of 67.7 and a standard deviation of 19.6, ranging from 1 to 98 (Table 1). Among the image components measured at pedestrian eye level, the mean shares of sidewalks, greenery, and vehicles were 4%, 17%, and 5%, respectively. The PSQI, which combines these components, had a mean of 0.00 and a standard deviation of 0.68, ranging from - 2.85 to 2.83.

Figure 2 presents street-view examples with contrasting PSQI values from Types B and A, both of which had high Walk Scores. The Type B examples in the top row have negative PSQI values, whereas the Type A examples in the bottom row have positive values. These examples illustrate the differences between the two indicators and are not interpreted as representative of streetscape conditions of either type as a whole.

The two indicators showed different spatial distributions (Fig. 3a, b). High Walk Scores formed contiguous areas in several central neighborhoods, whereas high and low PSQI scores were interspersed within these areas. Some block groups with relatively low Walk Scores exhibited higher PSQI values. Across the full sample, the correlation between Walk Score and PSQI was -0.36 , indicating that higher Walk Scores were generally associated with lower PSQI scores (Fig. 4a). Relationships with VLM-rated qualities differed by attribute. Walk Score was negatively correlated with the VLM-rated pleasant/inviting versus car-dominated score (Spearman's $\rho = -0.47$) and the well-maintained score ($\rho = -0.20$). In contrast, it was positively correlated with the interesting score ($\rho = 0.26$; Table S2). Thus, the overall relationship between the two measures and the relationships with individually rated qualities did not follow the same direction.

4.2 What Walk Score tracks at eye level

In the hierarchical OLS analysis, M1, which included socioeconomic characteristics and neighborhood urban structure variables, had an R^2 value of 0.587 (Table 2). R^2 increased to 0.606 in M2 after adding the GIS-based street-tree and sidewalk variables, to 0.639 in M3 after adding five physical eye-level attributes, and to 0.665 in M4 after adding three VLM-rated qualities. The increase in explanatory power at each stage was 1.9, 3.3, and 2.6 percentage points. The HC3-based block F-tests for the added variable sets were significant ($F = 44.4, 39.5$, and 56.6 , respectively; all $p < 0.001$). Compared with M2, which accounted for neighborhood characteristics and GIS variables, the final model, including both physical eye-level attributes and VLM-rated qualities, had 5.9 percentage points greater explanatory power.

Table 2
Model fit for hierarchical OLS regressions of Walk Score

Model	R ²	Adj. R ²	ΔR ²	Block F (HC3)	AIC
M1: Macro-level controls	0.587	0.586	—	394.0***	17,658.3
M2: + GIS inventories	0.606	0.604	0.019	44.4***	17,556.4
M3: + Eye-level physical attributes	0.639	0.637	0.033	39.5***	17,369.4
M4: + VLM-rated qualities	0.665	0.662	0.026	56.6***	17,210.4

N = 2,232. ΔR² is the increase over the preceding model; block F tests the joint significance of the variables added at each step (HC3 covariance). *** $p < 0.001$.

In the full model, the sidewalk view and VLM-rated well-maintained and interesting scores were positively associated with the Walk Score, whereas the VLM-rated pleasant/inviting versus car-dominated score was negatively associated. These four variables had the same direction and were statistically significant for OLS, SEM, and SAR (all $p < 0.01$; Table 3 and Figure S1). The unstandardized coefficients in the SEM, the main spatial model, were 48.883, 17.491, 34.387, and -20.353 , respectively. The results for the other physical attributes differed across models. The green view had a significant negative association and

visual complexity had a significant positive association in OLS and SAR, but neither was significant in SEM. Visual enclosure was significantly positively associated with Walk Score in the OLS model. Spatial autocorrelation remained in the residuals of the full OLS model (Moran's I = 0.494, $p = 0.002$). In SEM, the estimated spatial error coefficient was $\lambda = 0.906$ ($p < 0.001$), and residual Moran's I decreased to approximately zero and was not significant ($p = 0.492$). Spatial autocorrelation remained in the SAR residuals (Moran's I = 0.140; $p = 0.002$).

Table 3
Associations with Walk Score under OLS and spatial model specifications (N = 2,232)

Variable	M3 OLS Physical	M4 OLS Full	M4 SEM Full	M4 SAR Full
Constant	-30.954* (12.025)	-4.624 (12.868)	47.174*** (7.796)	-17.436* (8.077)
Macro-level controls				
Median household income (log)	1.022 (0.824)	0.735 (0.807)	-0.857 (0.527)	0.937 (0.501)
Latino (%)	-0.045*** (0.012)	-0.053*** (0.012)	0.031** (0.011)	-0.025** (0.008)
Owner-occupied (%)	-0.203*** (0.018)	-0.192*** (0.018)	-0.037*** (0.011)	-0.073*** (0.011)
Population density (log)	3.893*** (0.556)	2.759*** (0.577)	2.125*** (0.285)	1.876*** (0.326)
Land-use mix	7.908** (2.427)	8.069*** (2.364)	4.381*** (1.322)	5.552*** (1.474)
Bus stops within ¼ mile (log)	3.511*** (0.442)	3.133*** (0.421)	3.954*** (0.338)	1.368*** (0.261)
Park presence (0/1)	-4.234*** (0.782)	-4.027*** (0.762)	-1.635*** (0.388)	-1.978*** (0.458)
GIS inventories				
Street trees (GIS)	-0.325*** (0.039)	-0.287*** (0.040)	-0.266*** (0.022)	-0.203*** (0.023)
Sidewalk length (GIS)	-0.003* (0.001)	-0.004** (0.001)	-0.003*** (0.001)	-0.002* (0.001)
Eye-level physical attributes				
Visual enclosure	21.263*** (3.402)	16.589*** (3.529)	0.719 (2.617)	-0.460 (2.466)
Sidewalk view	62.658** (22.382)	78.935*** (22.533)	48.883*** (12.519)	44.244** (14.503)
Green view	-30.804*** (6.358)	-29.454*** (6.540)	-5.049 (3.531)	-9.755** (3.723)
Visual complexity	171.493*** (27.080)	151.249*** (30.309)	3.997 (15.548)	45.848* (18.245)
Vehicle view	69.868*** (15.889)	-4.918 (16.034)	2.394 (9.450)	-2.050 (10.861)

Variable	M3 OLS Physical	M4 OLS Full	M4 SEM Full	M4 SAR Full
VLM-rated qualities				
VLM: pleasant/inviting vs car-dominated		-52.376*** (4.884)	-20.353*** (3.106)	-21.657*** (3.185)
VLM: well maintained		19.021*** (4.248)	17.491*** (2.694)	12.466*** (2.602)
VLM: interesting		95.550*** (11.197)	34.387*** (7.021)	35.969*** (7.739)
λ (SEM) / ρ (SAR)			0.906*** (0.009)	0.675*** (0.013)
R ² / pseudo-R ²	0.639	0.665	0.558	0.853
AIC	17,369.4	17,210.4	15,262.8	15,629.1
Residual Moran's I (p)	—	0.494 (0.002)	-0.000 (0.492)	0.140 (0.002)

Unstandardized coefficients with standard errors in parentheses (HC3 for OLS; asymptotic for SEM and SAR). λ and ρ are the spatial error and lag parameters; SAR coefficients are model parameters rather than impacts. Pseudo-R² is the squared correlation between observed and predicted values. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

The results for the vehicle view differed depending on whether the VLM-rated qualities were included. In M3, which excluded VLM-rated qualities, the unstandardized vehicle-view coefficients were 69.868 in OLS, 27.341 in SEM, and 29.219 in SAR, with significant positive associations in all three models ($p < 0.01$; Table S4a). In M4, which added VLM-rated qualities, the coefficients decreased in absolute magnitude to 4.918, 2.394, and 2.050, respectively, and were not significant in any model (Table 3). Additional sensitivity analyses controlled for the violent event rate or separately restricted the sample to block groups with a population of at least 300, a Walk Score of at least 5, or at least 5 GSV sampling points. Across all four analyses, the positive associations of the sidewalk view and the VLM-rated well-maintained and interesting scores and the negative association of the VLM-rated pleasant/inviting versus car-dominated score remained significant ($p < 0.05$) (Table S4b).

4.3 Where the two measures diverge

Classification using the sample medians of Walk Score and PSQI, 71 and 0.01, identified 443 block groups (19.8%) as concordant high (A), with high values on both indicators; 695 (31.1%) as walkable on paper only (B), with high Walk Score and low PSQI; 673 (30.2%) as walkable on the street only (C), with low Walk Score and high PSQI; and 421 (18.9%) as concordant low (D), with low values on both indicators (Table 4). The two discordant types, B and C, comprised 1,368 block groups or 61.3% of the sample. Spatially, Type B occurred in several block groups in central Los Angeles and southern areas, whereas Type C was distributed across the San Fernando Valley and several western areas (Fig. 3c). The

continuous divergence index showed a similar pattern to the type map, with positive values in parts of the central and southern areas and negative values in several areas of the valley and west (Fig. 3d).

The relationship between the two indicators also differed by income group. Within the low-, middle-, and high-income groups defined using ACS 2013–2017 median household income, the correlations were – 0.05, – 0.14, and – 0.29, respectively, smaller in absolute magnitude than the full-sample correlation of – 0.36 (Fig. 4a). The linear relationship between the indicators was weak in the low-income group, whereas a relatively clear negative relationship remained in the high-income group. Mean values across 20 PSQI ventiles also showed that the mean Walk Score generally decreased and the mean block-group median household income tended to increase with higher PSQI (Fig. 4b).

Table 4
Block-group profiles by concordance between Walk Score and PSQI

Variable	A Concordant high	B Paper only	C Street only	D Concordant low
N (%)	443 (19.8%)	695 (31.1%)	673 (30.2%)	421 (18.9%)
Walk Score	82.5	82.3	48.6	58.5
PSQI (index units)	+ 0.48	-0.60	+ 0.60	-0.47
Sidewalk view (% of pixels)	5.3	3.6	4.5	3.3
Green view (% of pixels)	20.0	13.3	22.2	13.9
Vehicle view (% of pixels)	4.7	7.2	3.3	6.1
Block-group median household income (\$1,000)	94.3	57.7	124.5	67.6
Latino (%)	34.0	60.7	33.1	61.8
Non-Hispanic White (%)	39.7	16.7	45.4	16.2
Owner-occupied (%)	32.3	21.6	65.9	41.4
Poverty (%)	18.0	26.8	10.7	23.2
Violent-event rate (log)	2.75	3.14	2.07	2.89
Street trees (count)	14.0	12.0	22.4	18.7

Types are defined by the sample medians of Walk Score (71) and PSQI (0.01): A, high on both; B, high Walk Score and low PSQI; C, low Walk Score and high PSQI; D, low on both. Entries are means; the income row is the mean of block-group median household incomes. Violent-event rate is the log of 2015–2017 events per 1,000 residents.

4.4 Who lives where they diverge

The two discordant types differed in terms of physical streetscape conditions and socioeconomic characteristics (Table 4). Type B had a mean Walk Score of 82.3 and a mean PSQI of – 0.60, compared with 48.6 and 0.60 for Type C. Sidewalk view was 3.6% and 4.5% in Types B and C, respectively, green view was 13.3% and 22.2%, and vehicle view was 7.2% and 3.3%. The mean block-group median household income was \$57,700 in type B, lower than \$124,500 in Type C. The Latino population shares were 60.7% and 33.1%, owner-occupancy rates were 21.6% and 65.9%, and poverty rates were 26.8% and 10.7%, respectively. Across all four types, Type B had the lowest income and owner-occupancy rate, and the highest poverty rate and log-transformed violent-event rate. The Latino population share was also high for Type B, although it was higher for Type D (61.8%).

The regression models with the continuous divergence index as the dependent variable also showed relationships with socioeconomic characteristics (Table 5). In OLS, the divergence index was positively associated with Latino population share, population density, land-use mix, and the number of bus stops within ¼ mi and negatively associated with median household income, owner-occupancy rate, park presence, and GIS-based street-tree counts. The direction and statistical significance of these associations remained in the SEM model, except for land-use mix. The unstandardized SEM coefficients were – 0.261 for log median household income, 0.009 for the Latino population share, and – 0.012 for the owner-occupancy rate. The coefficients for log population density and the log-transformed number of bus stops within ¼ mi were 0.304 and 0.259, respectively, and those for park presence and street-tree counts were – 0.205 and – 0.015 (all $p < 0.001$). The spatial error coefficient was 0.666 ($p < 0.001$). After accounting for the other variables, block groups with lower income and owner-occupancy rates and higher Latino population shares had relatively higher Walk Scores than PSQI values.

Table 5
Associations with the signed divergence index

Variable	OLS (HC3)	SEM (ML)
Constant	-1.253 (1.142)	-0.215 (0.819)
Median household income (log)	-0.256** (0.082)	-0.261*** (0.065)
Latino (%)	0.008*** (0.001)	0.009*** (0.001)
Owner-occupied (%)	-0.021*** (0.002)	-0.012*** (0.001)
Population density (log)	0.466*** (0.057)	0.304*** (0.035)
Land-use mix	0.497* (0.206)	0.197 (0.168)
Bus stops within ¼ mile (log)	0.141*** (0.035)	0.259*** (0.039)
Park presence (0/1)	-0.340*** (0.061)	-0.205*** (0.051)
Street trees (GIS)	-0.015*** (0.003)	-0.015*** (0.003)
λ		0.666*** (0.020)
N	2,232	2,232
R ² / pseudo-R ²	0.630	0.614

Dependent variable: $D = z(\text{Walk Score}) - z(\text{PSQI})$; positive values indicate a relatively higher Walk Score than PSQI. Unstandardized coefficients with standard errors in parentheses (HC3 for OLS; asymptotic for SEM). * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

5. Discussion

5.1 Interpreting divergence across scales

The results suggest that the Walk Score and pedestrian eye-level streetscape conditions are related but do not represent the same environmental characteristics. Walk Score was negatively correlated with PSQI, but its relationship with individual eye-level attributes varied. After accounting for neighborhood characteristics and spatial dependence, the sidewalk view and VLM-rated well-maintained and interesting scores were positively associated with the Walk Score, whereas the VLM-rated pleasant/inviting versus car-dominated score was negatively associated. This can be understood as the Walk Score being positively related to some eye-level characteristics and negatively related to others, rather than indicating that it does not reflect eye-level conditions. Given that previous validations of the Walk Score focused mainly on destination accessibility and neighborhood urban structure (Carr et al., 2010; Duncan et al., 2011), this study contributes by examining these relationships separately for individual pedestrian-scale attributes. These findings are consistent with discussions on walkability as encompassing characteristics at multiple spatial scales and the need to interpret indicators within their measurement scope (Ewing & Handy, 2009; Forsyth, 2015; Hall & Ram, 2018).

These relationships in Los Angeles may be associated with urban conditions in which destination accessibility and car-oriented streetscapes coexist in the same places. The positive association between the vehicle view and Walk Score in the models excluding VLM-rated qualities was consistent with this interpretation. However, because the actual traffic volumes and parking configurations were not directly analyzed, this study could not identify the urban processes that produced these relationships. The associations between greenery and visual complexity were also not significant in the SEM; therefore, the results were not consistent across all eye-level attributes. The findings are therefore appropriately interpreted as indicating that high accessibility does not always coincide with favorable eye-level streetscape conditions. This is consistent with previous research reporting differences between macroscale and microscale walking environments in Los Angeles (Ki & Chen, 2023), and suggests that using both measures may help distinguish local walking environments in greater detail.

5.2 Socioeconomic implications of divergence

Discordance between the Walk Score and PSQI was also associated with socioeconomic characteristics. Type B, with a high Walk Score and a low PSQI, had lower income and owner-occupancy rates, and higher Latino population shares and poverty rates than Type C, which showed discordance in the opposite direction. Associations with income, owner-occupancy rate, and Latino population share remained in the spatial regression of the divergence index. These findings allow researchers to report on the relative advantages of disadvantaged areas in macroscale walkability and disadvantages in microscale streetscape conditions within the same spatial units (King & Clarke, 2015; Conderino et al., 2021; Thornton et al., 2016). This should not be interpreted as indicating the absence of macroscale accessibility advantages. Rather, this study found that the advantages of access to nearby destinations and the relative disadvantages of eye-level streetscape conditions can coexist in the same areas. These relationships represent the associations between area-level characteristics and do not imply that particular population groups produce environmental discordance.

These findings indicate the need to consider both accessibility and streetscape quality when assessing equity in walking environments. Even areas with high Walk Scores may require improvements related to sidewalks, greenery, and vehicle exposure, which are difficult to distinguish when assessing local walking environments using a single indicator. The map developed in this study can be used to identify areas for further field investigations. This could involve examining pedestrian space, greenery, and vehicle exposure in Type B, and constraints on destination accessibility and connectivity in Type C. However, the classification alone is insufficient for determining investment priorities or specific interventions. Planning decisions require an additional assessment of sidewalk conditions and continuity, traffic safety, pedestrian volumes, accessibility for people with mobility limitations, and residents' needs.

5.3 Limitations

This was an observational study linking data from different years within spatial units and could not identify the causal processes underlying the discordance between the two measures. Although spatial econometric models account for spatial dependence, differences related to unobserved neighborhood

characteristics or residential location choices may remain. The use of block groups also limits the ability to directly explain the differences between streets within areas or individuals' walking experiences. The timing and coverage of the data also present further limitations. Socioeconomic variables are based on the ACS 2013–2017 five-year estimates, and the analysis uses the 2010 census block group boundaries. The Walk Score refers to 2018 and the GSV dataset to 2022, leaving a gap of approximately four years between the two measures. The observed differences may therefore reflect both differences in measurement scope and intervening changes in streetscape conditions and cannot be interpreted as contemporaneous discordance. Mountainous areas and industrial areas without available data were also excluded; therefore, the results should be interpreted within the scope of the final analytic sample. Whether the relationships observed in Los Angeles also hold in other cities requires separate examination.

There are also limitations associated with the measurement and classification. The PSQI comprises a sidewalk view, green view, and reverse-coded vehicle view, representing physical aspects of walking environments without directly including pavement conditions, crossing facilities, or traffic speeds. The four types are relative classifications based on sample medians; therefore, their labels do not indicate absolute walking feasibility. The proportion of discordance may vary with the composition of the index and classification criteria. For the VLM-rated qualities, the scores and conditional relationships varied with prompt wording, limiting their generalizability to human assessments of walking comfort. Finally, because the actual walking behavior and health outcomes were not analyzed, the implications of the observed discordance for individuals' mobility or health are beyond the scope of this study.

6. Conclusion

This study examined the relationships between Walk Score and pedestrian eye-level streetscape conditions, the spatial distribution of their discordance, and the associated socioeconomic characteristics across 2,232 block groups in Los Angeles. After accounting for neighborhood characteristics and GIS variables, some eye-level attributes remained significantly associated with the Walk Score, although the direction differed across attributes. Based on the sample medians, 61.3% of all block groups fell into two discordant types, and the extent to which the Walk Score was relatively high compared to the PSQI was associated with income, population composition, and housing tenure. This study contributes to the literature by comparing walking environments at different scales within the same spatial units and examining their differences through both classification and a continuous divergence index.

These findings suggest the need to consider both accessibility information provided by the Walk Score and eye-level streetscape information when assessing neighborhood walking environments. Using these two measures together may help identify unmet streetscape improvement needs in areas with high accessibility. Further research should examine whether the results hold in other cities and under alternative classification criteria and assess the practical meaning of discordance between measures by linking field assessments, residents' perceptions, and actual walking behavior.

Declarations

Author Contribution

J.S. contributed to conceptualization, methodology, investigation, data curation, formal analysis, visualization, project administration, and writing of the original draft. N.L. contributed to conceptualization, investigation, formal analysis, and writing of the original draft. J.S. and N.L. reviewed and edited the manuscript. Both authors read and approved the final manuscript.

Data Availability

All data used in this study are publicly available from their original sources; however, the authors are not authorized to redistribute the datasets.

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Figures

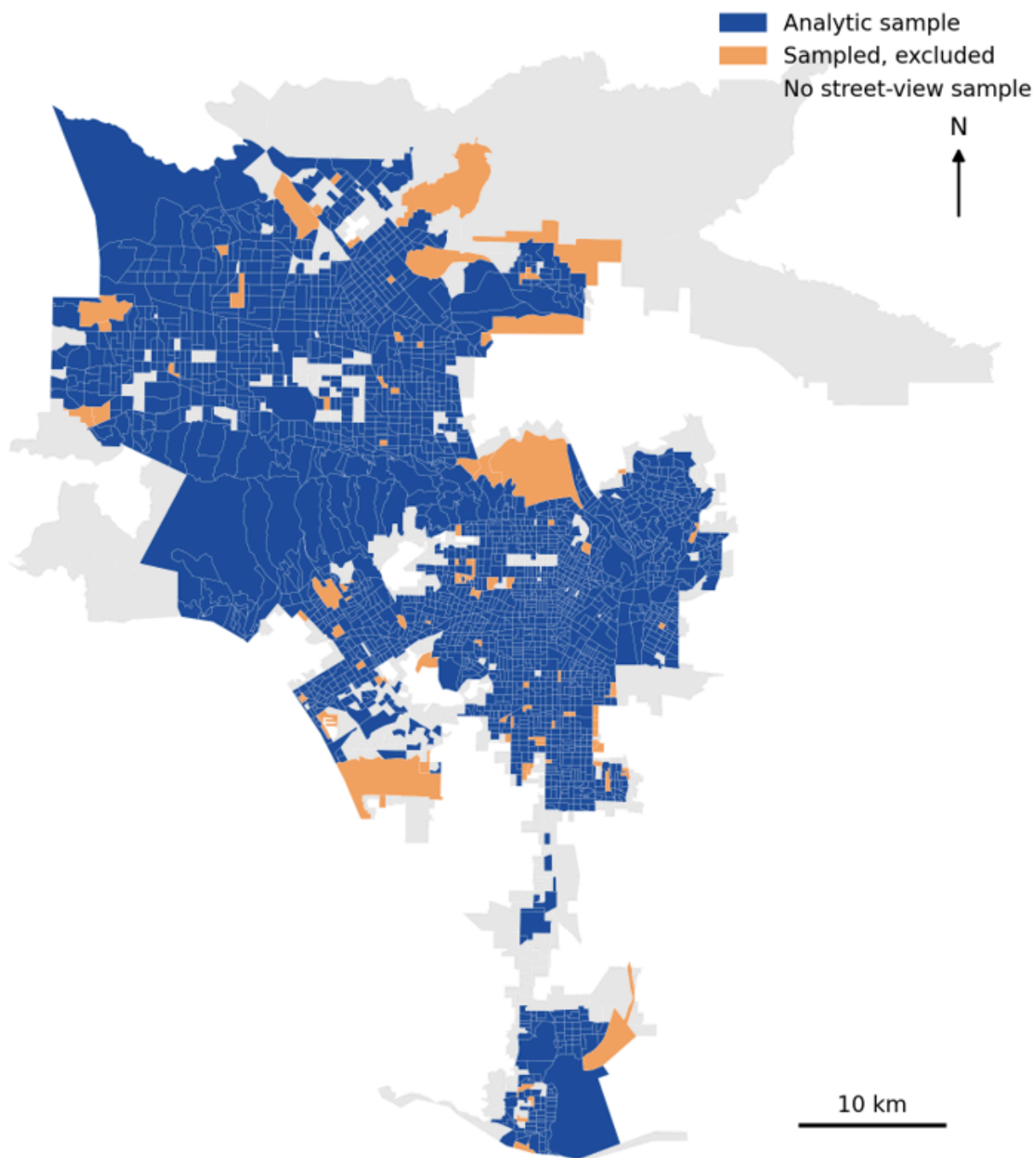


Figure 1

Study area and sample coverage

City of Los Angeles. 2010 census block-group boundaries. Analytical sample: 2,232; sampled but excluded: 99; without street-view sampling: 441. The exclusions reflected image quality, unscored Walk Scores, or missing socioeconomic controls.

Type B
walkable on
paper only



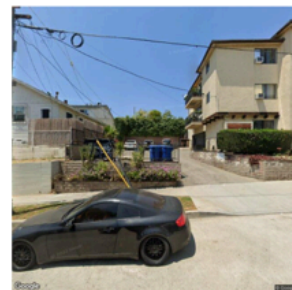
Walk Score 91 · PSQI -1.64



Walk Score 90 · PSQI -1.53

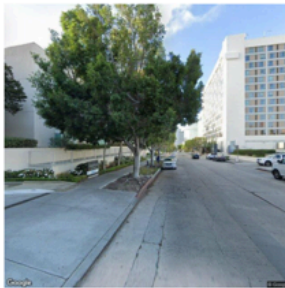


Walk Score 81 · PSQI -1.36



Walk Score 80 · PSQI -1.78

Type A
concordant
high



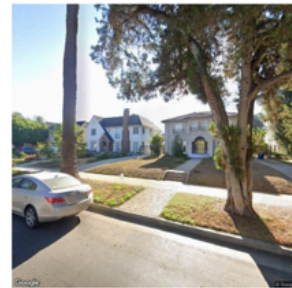
Walk Score 90 · PSQI +1.25



Walk Score 89 · PSQI +1.70



Walk Score 88 · PSQI +1.34



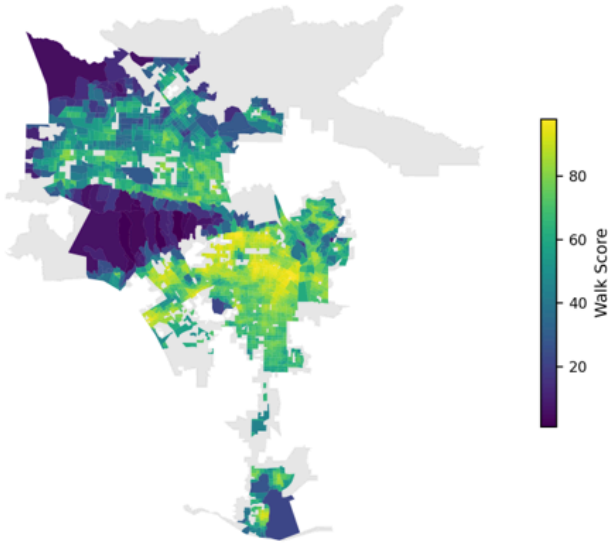
Walk Score 80 · PSQI +1.75

Figure 2

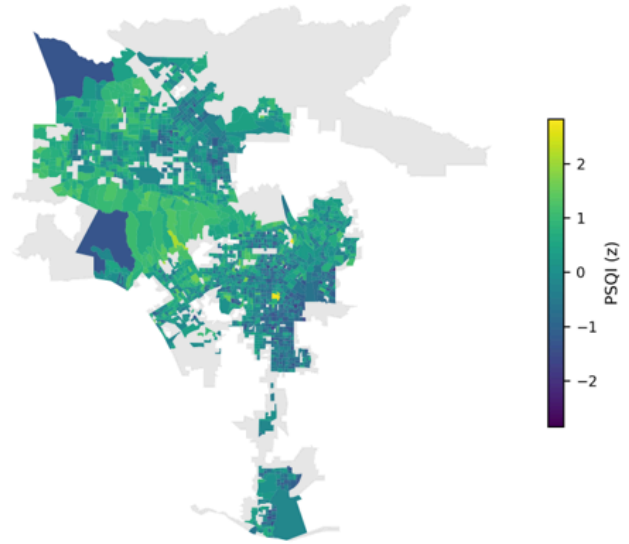
Street-view examples of high Walk Score with contrasting PSQI

Top row: Type B (walkable only on paper); bottom row: Type A (concordant high). The Walk Score and PSQI values are shown below each image. Type labels refer to sample-relative median-based classifications. The selected images illustrate contrast and are not representative of either type. Walk Score: 2018. Imagery: Google Street View (2022 dataset); attribution is retained in each panel.

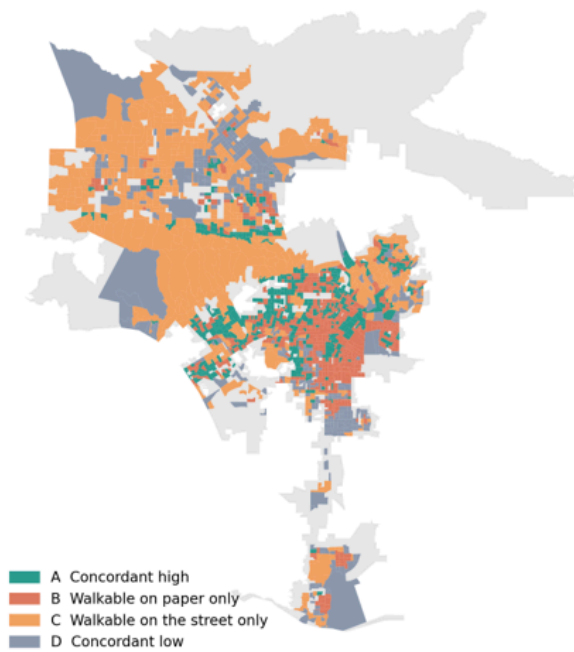
(a) Walk Score



(b) Pedestrian streetscape quality index



(c) Concordance typology



(d) Divergence index

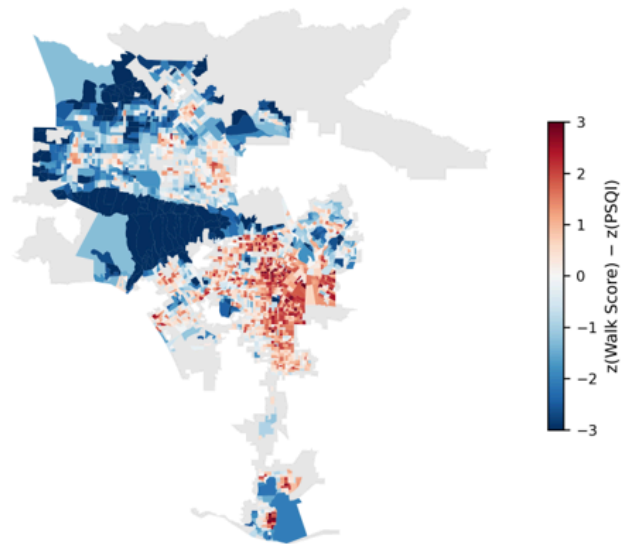


Figure 3

Spatial distributions of Walk Score, PSQI, and their divergence

(a) Walk Score; (b) PSQI, the mean of standardized component scores (the “z” label denotes this composite, not unit variance); (c) median-based types A–D; (d) $D = z(\text{Walk Score}) - z(\text{PSQI})$. $N = 2,232$. Light gray indicates block groups outside the analytic sample. Walk Score: 2018; GSV dataset: 2022.

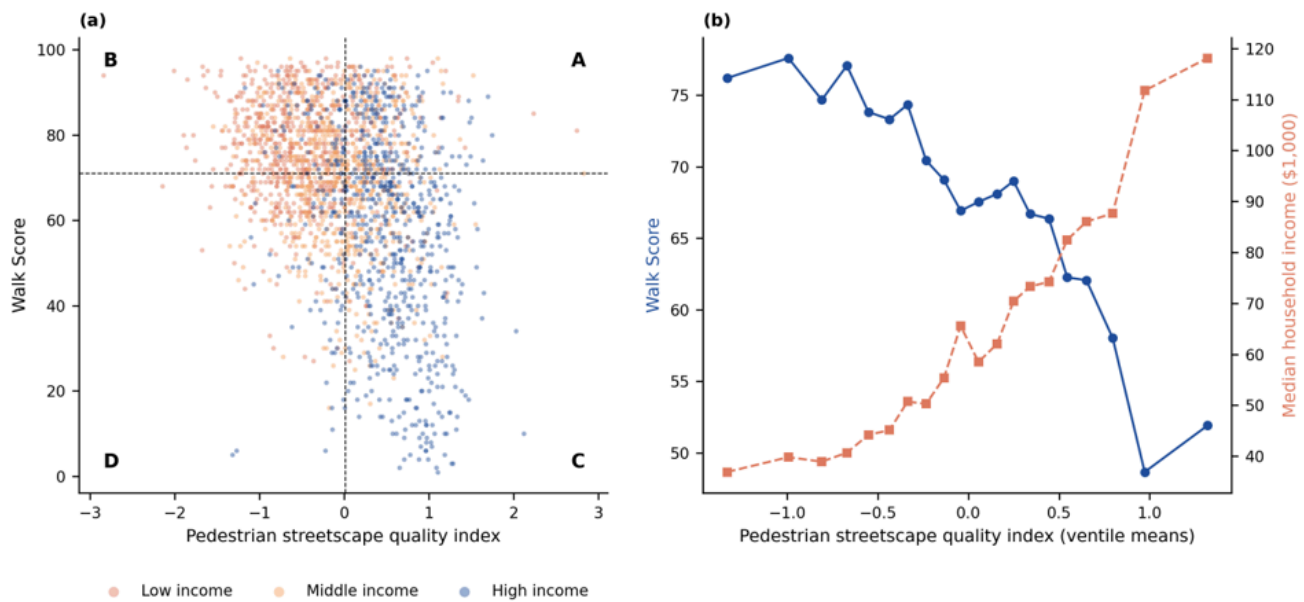


Figure 4

Walk Score and PSQI by income group and PSQI ventile

(a) Block groups by tertile of ACS 2013–2017 median household income. Dashed lines indicate the sample medians defining types A–D. Overall $r = -0.36$; within low-, middle-, and high-income tertiles, $r = -0.05$, -0.14 , and -0.29 . (b) Means of Walk Score and block-group median household income across 20 PSQI groups. $N = 2,232$. Walk Score: 2018; GSV dataset: 2022.