# Street View for Whom? An Initial Examination of Google Street View's Urban Coverage and Socioeconomic Indicators in the US


Zeyu Wang
Urban Design & Planning
University of Washington, USA
zeyuw1@uw.edu

Yingchao Jian
Electrical & Computer Engineering
University of Washington, USA
yingcj@uw.edu

Adam Visokay
Department of Sociology
University of Washington, USA
avisokay@uw.edu

Don MacKenzie
Civil & Environmental Engineering
University of Washington, USA
dwhm@uw.edu

Jon E. Froehlich
Allen School of Computer Science
University of Washington, USA
jonf@cs.uw.edu


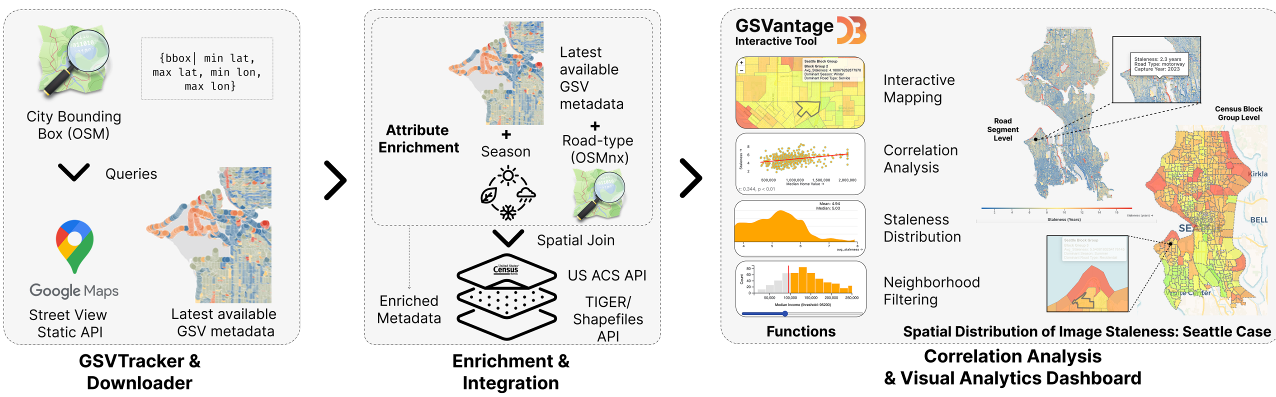


**Figure 1: Automated pipeline that analyzes associations between GSV coverage and socioeconomic indicators.**


## Abstract

Street-level imagery is foundational to modern urban informatics research; however, bias from systematic differences in *where* and *when* images are captured can obscure important relationships and impact study findings. We examine how Google Street View (GSV) spatio-temporal capture patterns correlate with ACS socioeconomic indicators and also provide a reproducible, open-source data analysis pipeline and dashboard. To demonstrate and evaluate our approach, we study four US cities computing correlation coefficients between image staleness and social-demographic, mobility, and housing-related variables. Our findings demonstrate systematic spatial disparities in GSV coverage: neighborhoods characterized by urban density and diverse demographics tend to have more current imagery, whereas areas with suburban or higher-income profiles frequently lag behind.



## CCS Concepts

• **Information systems → Geographic information systems**.




ACM ISBN 979-8-4007-2182-3/2025/11
https://doi.org/10.1145/3764919.3770883



## Keywords

Urban Informatics; Street-level Imagery; Biases

**ACM Reference Format:**
Zeyu Wang, Yingchao Jian, Adam Visokay, Don MacKenzie, and Jon E. Froehlich. 2025. Street View for Whom? An Initial Examination of Google Street View's Urban Coverage and Socioeconomic Indicators in the US. In *The 4th ACM SIGSPATIAL International Workshop on Spatial Big Data and AI for Industrial Applications (GeoIndustry '25), November 3–6, 2025, Minneapolis, MN, USA.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3764919.3770883


## 1 Introduction

Street-level imagery from services like *Meta Mapillary*, *Google Street View* (GSV), or *Apple Lookaround* have become foundational to urban informatics, supporting diverse research in urban planning, infrastructure monitoring, neighborhood audits, and real estate analytics [6, 8, 12, 15, 21, 26]. With over 220 billion images across 100+ countries, GSV has become particularly influential due to its geographic coverage [2, 14], accessibility, and high-resolution panoramic images [3, 6, 14]. Researchers leverage GSV imagery to investigate urban environments [17, 19], perform virtual audits [4, 23, 24], and extract detailed environmental and infrastructural features at scale [6, 20, 22]. Despite GSV's widespread adoption and practical utility, disparities in how frequently or recently these images are updated across neighborhoods and cities remain largely unexamined [1, 18]. Such disparities may reflect and exacerbate deeper inequalities in the digital representation of urban spaces, potentially biasing downstream analyses and influencing policy decisions.

In this paper, we investigate how the recency and frequency of GSV image captures correlate with socioeconomic conditions at the neighborhood level. We define image "stalenes" as the elapsed time since the most recently available panoramic image was captured at a given location. Using Atlanta, Chicago, Detroit, and Seattle as illustrative case studies, we examine how GSV metadata corresponds with comprehensive socioeconomic and demographic indicators drawn from the U.S. Census American Community Survey (ACS) 5-year estimates [25].

We find image staleness is associated with several sociodemographic indicators including population density, median income, and racial composition. To facilitate transparent and intuitive exploration of potential spatial disparities, we developed a modular, reproducible, and open-source web-based interactive mapping platform called *GSVantage* (Figure 1). This platform allows researchers, policymakers, and public stakeholders to dynamically explore spatial patterns in GSV image staleness, compare neighborhood conditions, and identify systematic gaps in digital visibility. Users can filter neighborhoods based on socioeconomic thresholds, visualize relationships between staleness and demographic attributes through linked scatter plots, and conduct comparative analyses within and across different urban contexts.

Our contributions are threefold: we provide (1) empirical evidence of spatial inequities in widely used street-level imagery, filling a gap in urban informatics research; (2) an open-source, extensible framework[1] for integrating imagery metadata with socioeconomic data across diverse contexts; and (3) an interactive visualization tool that promotes transparency and supports audits of digital equity, thereby supporting informed urban policy and planning decisions.

## 2 Related Work

We situate our work in data biases in maps and techniques to measure and study street view imagery (SVI) coverage.

**Data Biases in Maps**. Digital inequity in mapping and visualization technologies is well documented, revealing that traditionally under-served or low-income communities often suffer from both spatial and temporal gaps in the availability and quality of street-level data [11, 16]. These spatial disparities reflect broader patterns of digital participation inequality, where volunteer contributors are predominantly concentrated in affluent, technologically connected communities.

**SVI Image Coverage**. Prior work in street-view imagery (SVI) coverage examines both spatial completeness [5] and temporal consistency [7], yet these studies remain constrained by limited geographic reach and depth of analysis. Badland et al. [5] validate virtual streetscape audits using observations conducted on site, while Curtis et al. [7] analyze gaps in GSV coverage in space and in time across five U.S. cities. They find lags that span several years disproportionately affecting economically disadvantaged neighborhoods. More recent studies have expanded geographic coverage [11, 18] while others examine the spatial representation of specific elements in street-level imagery [9].

[1]https://github.com/makeabilitylab/GSVantage

Despite recent progress, several critical gaps remain. First, existing studies lack scalable and reproducible analytical frameworks capable of integrating standardized demographic data (e.g., ACS) with SVI metadata across diverse urban contexts, resulting in analyses that remain limited to specific cities or regions and lack methodological consistency for broader application. Second, current research has not prioritized the development of accessible, interactive tools that enable transparent exploration of digital equity patterns for researchers and practitioners. Our research fills these gaps by developing a scalable framework that integrates GSV metadata with standardized ACS data at the census block group level, enabling comparisons across diverse American urban contexts while providing an interactive web-based platform for transparent exploration of spatial disparities.

## 3 Analysis Pipeline and Study Method

To examine how SVI staleness varies with neighborhood characteristics, we designed and developed a custom, open-source three-stage analysis pipeline that: (1) ingests and cleans GSV metadata; (2) enriches each panorama with road-type and season attributes and aggregates them to census units; (3) links 2023 ACS socioeconomic data via the Census API to perform correlation analysis and generate spatial visualizations of imagery staleness and neighborhood characteristics. The pipeline is implemented in Python using *GeoPandas*, *OSMnx*, and *Requests*. Below, we describe our method applied to four US cities: Atlanta (347 km$^2$), Chicago (606 km$^2$), Detroit (370 km$^2$), and Seattle (217 km$^2$).

**Stage 1: Downloader.** For downloading GSV metadata, we developed a novel tool [10] that retrieves GSV metadata using the GSV Static API given a *city name*, a *grid cell size*, and an optional *bounding box grid size* (if the latter is not supplied, we use *Nominatim* to auto-generate the city's bounding box from OSM data). The tool discretizes a given city into a `<lat, lng>` grid and queries the GSV Static API for the closest pano at each `<lat, lng>` grid point. Due to API constraints, the tool downloads metadata only about the most recent imagery available. Thus, we are unable to conduct historical frequency analysis—*i.e.,* how many images have been captured at a selected point over time. Instead, we focus on "*staleness*", which we define as the elapsed time between the most recent imagery capture date and the current date. The retrieved geospatial coordinates and timestamps are stored in a *GeoDataFrame*.

**Stage 2: Spatial Aggregation.** Stage 2 contextualizes each SV image with road-type information, derived from *OSMnx*, and season attributes, inferred from the capture timestamp, and also performs a spatial categorization. For the latter, we use the 2023 *TIGER/Line* boundary shapefiles for U.S. Census block groups or tracts. Each enriched point is assigned to its containing geographic unit and aggregated at the chosen level to compute the mean imagery staleness, the dominant capture season along with its relative frequency, and the most common road type category with its prevalence. Subsequently, we retrieve 2023 data from the U.S. Census ACS 5 year API on population, median household income, ratio of non white residents, commuting mode shares (walking, bicycling, public transit), vehicle ownership and median home value. Our pipeline parses the JSON into a *DataFrame* and calculates additional indicators such as population density per square kilometer, single family housing share, and no vehicle household ratio. These ACS variables are then merged via the *GEOID* identifier with the Stage 2 aggregates. Finally, the enriched GeoDataFrame is prepared for export to support downstream analyses and power the backend of our dashboard that assesses how imagery staleness, seasonality, and road-type distribution vary with neighborhood socioeconomic characteristics.

**Stage 3: Quantitative Analysis and Dashboard.** To quantify the relationship between neighborhood socioeconomic measures $X$ and Street View image staleness $Y$, we compute Pearson correlation coefficients. We exclude any block groups with avg_staleness $\leq 0$ or invalid socioeconomic values (*e.g.,* median income $\leq 0$, missing data, or population density $< 0$). To capture the degree of similarity in these correlation patterns across cities, we define a *consistency score* for each variable $v$ as:

$$C_v = \frac{1}{1 + \mathrm{sd}\big(r_{v,\mathrm{Seattle}},\ r_{v,\mathrm{Detroit}},\ r_{v,\mathrm{Atlanta}},\ r_{v,\mathrm{Chicago}}\big)},$$

where $\mathrm{sd}(\cdot)$ denotes the sample standard deviation across the four city-specific Pearson $r$ values. A consistency scores of 1 indicates that a variable's correlation direction and magnitude are uniform across all cities.

For intuitive exploration and transparent dissemination of these analytical outcomes, we then developed an interactive web-based dashboard using *D3.js* and the *Observable* framework. The platform supports dynamic filtering by demographic thresholds, spatial mapping of staleness patterns, synchronized scatter-plot comparisons, and on-the-fly visual analysis of the links between socioeconomic conditions and imagery recency. Designed for modularity and reproducibility, the framework can be easily extended to other cities with minimal input-data adjustments.

In sum, a primary strength of our method lies in its modular and generalizable design. By relying solely on standardized public data sources (GSV static API, ACS and OSM), our approach ensures methodological consistency and facilitates replication across various urban contexts. Furthermore, the Python-based analytical pipeline, combined with interactive visualizations, supports rapid scalability, enabling systematic audits of street-level imagery recency and potential disparities in digital visibility across diverse geographic settings.

## 4 Results

Across all four metropolitan areas studied, we observe a generally consistent "digital redlining" pattern in Google's SVI update frequency. Neighborhoods that are higher-income, higher-value, predominantly single-family, or suburban tend to exhibit higher image staleness while denser, pedestrian-oriented, and higher-minority communities receive more regular updates. Among the variables tested, **Walk Commute Share** emerges as the most robust and consistent predictor of update frequency across all cities. Notably, **Detroit** stands out as an exception, with generally weaker and more variable correlations, suggesting that local demographic or operational factors may be moderating the broader trend. To provide a more intuitive view of the spatial distribution of image staleness, we use Seattle as an example (Figure 1).

In detail, we retain sufficient observations (N) for each city ($N_{\mathrm{Atlanta}} = 425$, $N_{\mathrm{Chicago}} = 2142$, $N_{\mathrm{Detroit}} = 622$, $N_{\mathrm{Seattle}} = 537$) after filtering, ensuring adequate statistical power. Figure 2a presents a heatmap of Pearson correlation coefficients ($r$) across seven variables and Figure 2c present the correlation landscape with significance for each city. across seven variables. In **Seattle** and **Chicago**, both *median income* and *median home value* exhibit positive correlations with staleness (e.g., $r_{\mathrm{MHV}} = 0.344$, $r_{\mathrm{MI}} = 0.276$ in Seattle), indicating that wealthier areas tend to have older imagery. In contrast, *non-white ratio* and *population density* show negative correlations (*e.g.,* $r_{\mathrm{NWR}} = -0.282$, $r_{\mathrm{PD}} = -0.197$ in Seattle), suggesting more frequent updates in denser and more racially diverse neighborhoods. In **Atlanta**, population density correlates negatively with staleness ($r = -0.281$, $p < 0.001$), while the single-family ratio correlates positively ($r = 0.230$, $p < 0.05$), consistent with slower updates in suburban areas. **Detroit**, however, diverges from this pattern: population density and median build year correlate modestly *positively* with staleness ($r = 0.175$ and $r = 0.154$, both $p < 0.01$), and all other socioeconomic variables exhibit weak or nonsignificant correlations ($|r| < 0.05$, $p > 0.05$).

Variable-level consistency scores across cities further reinforce these patterns. As shown in Figure 2b, *Walk Commute Share* achieves the highest consistency score ($C_{\mathrm{WCS}} \approx 0.92$), reflecting a uniformly negative relationship with staleness. *Median Build Year* also scores highly ($C_{\mathrm{MBY}} \approx 0.91$), as do *non-white ratio* ($C_{\mathrm{NWR}} \approx 0.85$) and *population density* ($C_{\mathrm{PD}} \approx 0.83$). By contrast, *median income*, *home value*, and *single-family ratio* show slightly lower consistency scores (approximately 0.81–0.83), reflecting more variable relationships across cities (*e.g.,* positive in Seattle, near 0 in Detroit).

Finally, a multivariate regression on the combined dataset confirms that all predictors except median income ($p > 0.3$) are significantly associated with imagery staleness when controlling for one another ($\alpha = 0.05$). This supports the conclusion that image update disparities align closely with known patterns of spatial and socioeconomic inequality.

## 5 Discussion and Conclusion

In this work, we introduce a novel pipeline for assessing coverage bias in the recency of publicly available Google Street View (GSV) and Census APIs across socioeconomically varied neighborhoods. Our approach computes Pearson correlations between key socioeconomic indicators (e.g., median income, population density) and image staleness using high-quality North American Census APIs. Our findings have important implications for researchers relying upon SVI data instead of in-person audits, as bias can be propagated into downstream analysis without correction [13].

We also developed **GSVantage**, an interactive dashboard that maps spatial staleness patterns, enables synchronized scatterplot comparisons, and allows filtering based on user-selected demographic thresholds. Our case studies reveal statistically significant evidence of "digital redlining": higher-income, higher-value suburbs tend to have older imagery compared to denser, more pedestrian-oriented areas. Interestingly, this contrasts with some findings from Latin American cities [11], suggesting contingencies that warrant future research. The modular framework can be extended to other cities with minimal input adjustments; however, researchers outside the US may need to identify analogous census-data APIs as alternatives. Our code and datasets are publicly available on GitHub.

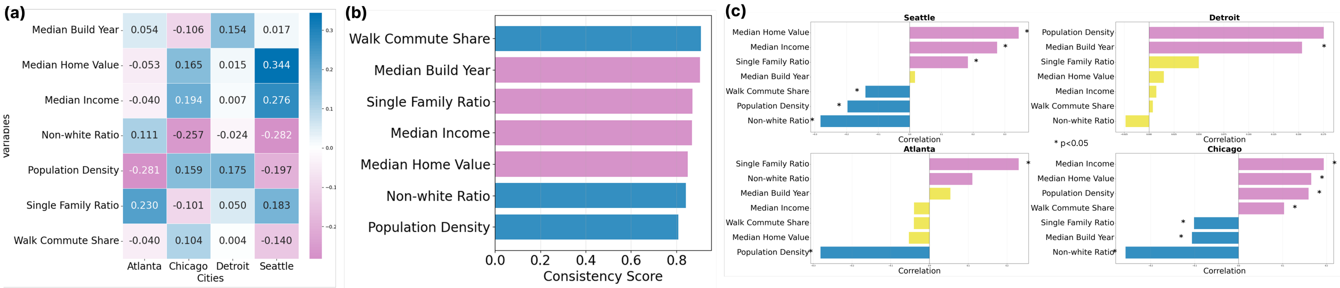


**Figure 2: GSV staleness *vs.* socioeconomic variables: (a) heatmap of correlations, (b) consistency across cities, and (c) city-wise correlations. In (b) and (c), colors denote correlation direction (blue = *Attention*, pink = *Neglect*, yellow = neutral); asterisks mark significant ($p < 0.05$).**

## Acknowledgments

We thank Dr. Jeffrey Heer for his feedback on *GSVantage*. This work was supported by NSF grant #2411222. Adam acknowledges the resources provided by the International Max Planck Research School for Population, Health and Data Science (IMPRS-PHDS).

## References

[1] Tim Alpherts, Sennay Ghebreab, and Nanne Van Noord. 2025. Artifacts of Idiosyncracy in Global Street View Data. *arXiv preprint arXiv:2505.11046* (2025).
[2] Dragomir Anguelov, Carole Dulong, Daniel Filip, Christian Frueh, Stéphane Lafon, Richard Lyon, Abhijit Ogale, Luc Vincent, and Josh Weaver. 2010. Google street view: Capturing the world at street level. *Computer* 43, 6 (2010), 32–38.
[3] Dragomir Anguelov, Carole Dulong, Daniel Filip, Christian Frueh, Stéphane Lafon, Richard Lyon, Abhijit Ogale, Luc Vincent, and Josh Weaver. 2010. Google Street View: Capturing the World at Street Level. *Computer* 43, 6 (June 2010), 32–38. doi:10.1109/MC.2010.170 Number: 6 Conference Name: Computer.
[4] Sajad Askari, Devon Snyder, Chu Li, Michael Saugstad, Jon E. Froehlich, and Yochai Eisenberg. 2025. Validating Pedestrian Infrastructure Data: How Well Do Street-View Imagery Audits Compare to Government Field Data? *Urban Science* 9, 4 (2025). doi:10.3390/urbansci9040130
[5] Hannah M. Badland, Simon Opit, Karen Witten, Robin A. Kearns, and Suzanne Mavoa. 2010. Can Virtual Streetscape Audits Reliably Replace Physical Streetscape Audits? *Journal of Urban Health* 87, 6 (Dec. 2010), 1007–1016. doi:10.1007/s11524-010-9505-x
[6] Filip Biljecki and Koichi Ito. 2021. Street view imagery in urban analytics and GIS: A review. *Landscape and Urban Planning* 215 (Nov. 2021), 104217. doi:10.1016/j.landurbplan.2021.104217
[7] Jacqueline W. Curtis, Andrew Curtis, Jennifer Mapes, Andrea B. Szell, and Adam Cinderich. 2013. Using google street view for systematic observation of the built environment: analysis of spatio-temporal instability of imagery dates. *International Journal of Health Geographics* 12, 1 (Dec. 2013), 53. doi:10.1186/1476-072X-12-53
[8] Shaoqing Dai, Yuchen Li, Alfred Stein, Shujuan Yang, and Peng Jia. 2024. Street view imagery-based built environment auditing tools: a systematic review. *International Journal of Geographical Information Science* 38, 6 (June 2024), 1136–1157. doi:10.1080/13658816.2024.2336034
[9] Zicheng Fan, Chen-Chieh Feng, and Filip Biljecki. 2025. Coverage and bias of street view imagery in mapping the urban environment. *Computers, Environment and Urban Systems* 117 (April 2025), 102253. doi:10.1016/j.compenvurbsys.2025.102253
[10] Jon E. Froehlich. 2025. GSV City Coverage Analysis Tool. https://jonfroehlich.github.io/gsv-tracker/www/ Accessed: 2025-10-06.
[11] Dustin Fry, Stephen J. Mooney, Daniel A. Rodríguez, Waleska T. Caiaffa, and Gina S. Lovasi. 2020. Assessing Google Street View Image Availability in Latin American Cities. *Journal of Urban Health* 97, 4 (Aug. 2020), 552–560. doi:10.1007/s11524-019-00408-7
[12] Timnit Gebru, Jonathan Krause, Yilun Wang, Duyun Chen, Jia Deng, Erez Lieberman Aiden, and Li Fei-Fei. 2017. Using deep learning and Google Street View to estimate the demographic makeup of neighborhoods across the United States. *Proceedings of the National Academy of Sciences* 114, 50 (Dec. 2017), 13108–13113. doi:10.1073/pnas.1700035114 Number: 50 Publisher: Proceedings of the National Academy of Sciences.
[13] Kentaro Hoffman, Stephen Salerno, Awan Afiaz, Jeffrey T. Leek, and Tyler H. McCormick. [n. d.]. Do We Really Even Need Data? *arXiv:2401.08702* ([n. d.]).
[14] Yujun Hou, Matias Quintana, Maxim Khomiakov, Winston Yap, Jiani Ouyang, Koichi Ito, Zeyu Wang, Tianhong Zhao, and Filip Biljecki. 2024. Global Streetscapes—A comprehensive dataset of 10 million street-level images across 688 cities for urban science and analytics. *ISPRS Journal of Photogrammetry and Remote Sensing* 215 (2024), 216–238.
[15] Koichi Ito and Filip Biljecki. 2021. Assessing bikeability with street view imagery and computer vision. *Transportation Research Part C: Emerging Technologies* 132 (Nov. 2021), 103371. doi:10.1016/j.trc.2021.103371
[16] Levente Juhász and Hartwig H. Hochmair. 2016. User Contribution Patterns and Completeness Evaluation of Mapillary, a Crowdsourced Street Level Photo Service. *Transactions in GIS* 20, 6 (2016), 925–947. doi:10.1111/tgis.12190 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/tgis.12190.
[17] Jian Kang, Marco Körner, Yuanyuan Wang, Hannes Taubenböck, and Xiao Xiang Zhu. 2018. Building instance classification using street view images. *ISPRS Journal of Photogrammetry and Remote Sensing* 145 (2018), 44–59. doi:10.1016/j.isprsjprs.2018.02.006 Deep Learning RS Data.
[18] Junghwan Kim and Kee Moon Jang. 2023. An examination of the spatial coverage and temporal variability of Google Street View (GSV) images in small- and medium-sized cities: A people-based approach. *Computers, Environment and Urban Systems* 102 (June 2023), 101956. doi:10.1016/j.compenvurbsys.2023.101956
[19] Xiaojiang Li, Chuanrong Zhang, Weidong Li, Robert Ricard, Qingyan Meng, and Weixing Zhang. 2015. Assessing street-level urban greenery using Google Street View and a modified green view index. *Urban Forestry & Urban Greening* 14, 3 (Jan. 2015), 675–685. doi:10.1016/j.ufug.2015.06.006
[20] Xinlei Liu, Kevin Wu, Minchu Kulkarni, Michael Saugstad, Peyton Anton Rapo, Jeremy Freiburger, Maryam Hosseini, Chu Li, and Jon E. Froehlich. 2024. Towards Fine-Grained Sidewalk Accessibility Assessment with Deep Learning: Initial Benchmarks and an Open Dataset. In *Proceedings of the 26th International ACM SIGACCESS Conference on Computers and Accessibility* (St. John's, NL, Canada) *(ASSETS '24)*. Association for Computing Machinery, New York, NY, USA, Article 103, 12 pages. doi:10.1145/3663548.3688531
[21] Yingjie Liu, Zeyu Wang, Siyi Ren, Runying Chen, Yixiang Shen, and Filip Biljecki. 2025. Physical urban change and its socio-environmental impact: Insights from street view imagery. *Computers, Environment and Urban Systems* 119 (2025), 102284.
[22] John O'Meara, Jared Hwang, Zeyu Wang, Mikey Saugstad, and Jon E. Froehlich. 2025. RampNet: A Two-Stage Pipeline for Bootstrapping Curb Ramp Detection in Streetscape Images from Open Government Metadata. In *Proceedings of the ICCV'25 Workshop on Vision Foundation Models and Generative AI for Accessibility: Challenges and Opportunities* (Honolulu, Hawaii). 10 pages. https://arxiv.org/abs/2508.09415
[23] Andrew G. Rundle, Michael D.M. Bader, Catherine A. Richards, Kathryn M. Neckerman, and Julien O. Teitler. 2011. Using Google Street View to Audit Neighborhood Environments. *American Journal of Preventive Medicine* 40, 1 (2011), 94–100. doi:10.1016/j.amepre.2010.09.034
[24] Manaswi Saha, Michael Saugstad, Hanuma Teja Maddali, Aileen Zeng, Ryan Holland, Steven Bower, Aditya Dash, Sage Chen, Anthony Li, Kotaro Hara, et al. 2019. Project sidewalk: A web-based crowdsourcing tool for collecting sidewalk accessibility data at scale. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–14.
[25] U.S. Census Bureau. 2023. American Community Survey 5-Year Estimates, 2018–2023. https://data.census.gov/cedsci/. Accessed: 2025-05-01.
[26] Zeyu Wang, Koichi Ito, and Filip Biljecki. 2024. Assessing the equity and evolution of urban visual perceptual quality with time series street view imagery. *Cities* 145 (Feb. 2024), 104704. doi:10.1016/j.cities.2023.104704