

# Street View for Whom?

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

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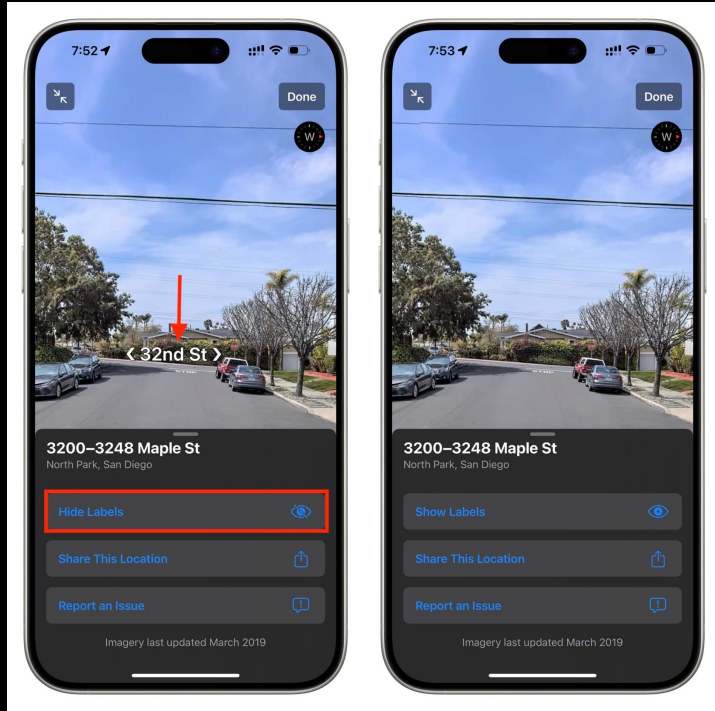
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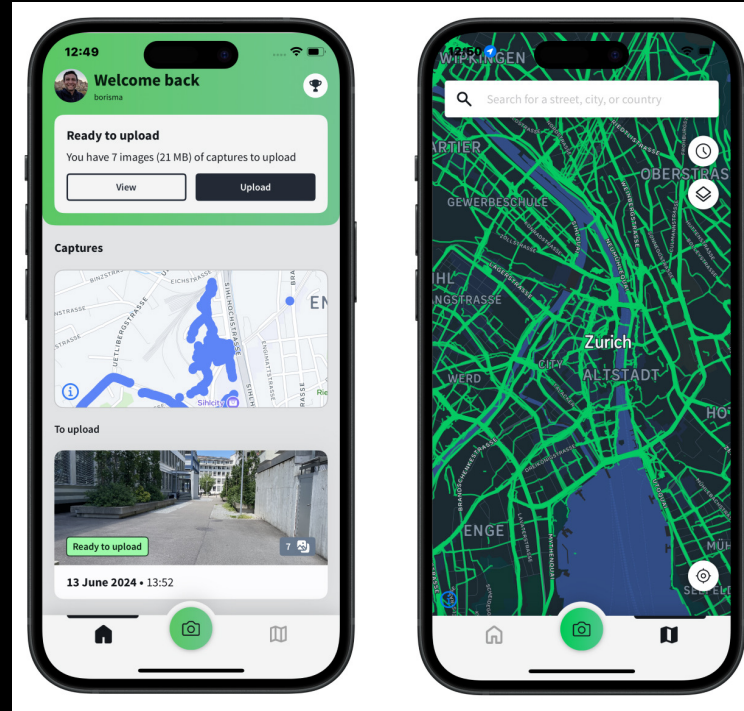


**STREET-LEVEL IMAGERY HAS BECOME FUNDAMENTAL  
TO URBAN INFORMATICS, SUPPORTING DIVERSE  
RESEARCH ACROSS VARIOUS FIELDS.**

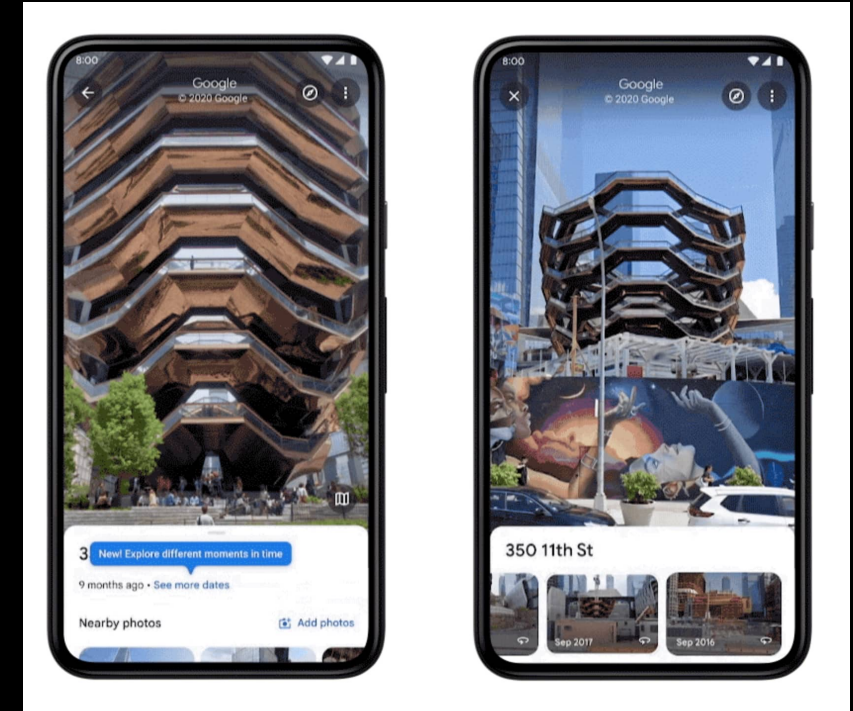
# MAJOR PROVIDERS



Apple Lookaround



Mapillary (Meta)



Google Street View

Also have...

BaiduMaps, KartaView, Grabmaps, etc.



KartaView

GrabMaps

**WITH**

**OVER 220 BILLION IMAGES  
ACROSS 100+ COUNTRIES**

**Google Street View (GSV) have become particularly  
influential due to its geographic coverage.**



Assessing the equity and evolution of urban visual perceptual quality with time series street view imagery

Zeyu Wang<sup>a</sup>, Koichi Ito<sup>a</sup>, Filip Biljecki<sup>a,b,\*</sup>

Research Paper

Measuring human perceptions of a large-scale urban region using machine learning

Fan Zhang<sup>a,b,c</sup>, Bolei Zhou<sup>d</sup>, Liu Liu<sup>e</sup>, Yu Liu<sup>a</sup>, Helene H. Fung<sup>f</sup>, Hui Lin<sup>b,g,\*</sup>, Carlo Ratti<sup>c</sup>

ARTICLE IN PRESS

Physical urban change and its socio-environmental impact: Insights from street view imagery

Yingjie Liu<sup>a,1</sup>, Zeyu Wang<sup>b,1</sup>, Siyi Ren<sup>c</sup>, Runying Chen<sup>c</sup>, Yixiang Shen<sup>d</sup>, Filip Biljecki<sup>e,f,\*</sup>

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Keywords:  
 Urban renewal  
 Gentrification  
 Change detection  
 Deep learning

Tohme: Detecting Curb Ramps in Google Street View Using Crowdsourcing, Computer Vision, and Machine Learning

Kotaro Hara<sup>1,2</sup>, Jin Sun, Robert Moore<sup>1,2</sup>, David Jacobs, Jon E. Froehlich<sup>1,2</sup>  
<sup>1</sup>Makeability Lab | <sup>2</sup>Human Computer Interaction Lab (HCIL)  
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GSV has been leveraged by researchers to sense urban environment, perform virtual audits at scale.

Using deep learning and Google Street View to estimate the demographic makeup of neighborhoods across the United States

Timnit Gebru<sup>a,1</sup>, Jonathan Krause<sup>a</sup>, Yilun Wang<sup>a</sup>, Duyun Chen<sup>a</sup>, Jia Deng<sup>b</sup>, Erez Lieberman Aiden<sup>c,d,e</sup>, and Li Fei-Fei<sup>a</sup>

<sup>a</sup>Artificial Intelligence Laboratory, Computer Science Department, Stanford University, Stanford, CA 94305; <sup>b</sup>Vision and Learning Laboratory, Computer Science and Engineering Department, University of Michigan, Ann Arbor, MI 48109; <sup>c</sup>The Center for Genome Architecture, Department of Genetics, Baylor College of Medicine, Houston, TX 77030; <sup>d</sup>Department of Computer Science, Stanford University; <sup>e</sup>Department of Computer Science, Stanford University

Edited by Kenneth

The United States is a diverse nation with a wide range of cultural, linguistic, and ethnic groups. Understanding the demographic makeup of neighborhoods is crucial for urban planning and policy-making. Although traditional methods of data collection, such as census and surveys, provide valuable insights, they often lack the granularity and timeliness needed to capture the dynamic nature of urban environments. In this paper, we present a novel approach to estimating the demographic makeup of neighborhoods using deep learning and Google Street View (GSV) imagery. Our method leverages the power of deep learning to automatically detect and classify demographic features in GSV images, such as building styles, street layouts, and vegetation. We compare our results to traditional methods and find that our approach significantly outperforms them in terms of accuracy and scalability. Our findings suggest that GSV imagery can be a valuable tool for understanding the demographic makeup of neighborhoods and for informing urban planning and policy-making.

PNAS

RESEARCH ARTICLE | SOCIAL SCIENCES  
 SUSTAINABILITY SCIENCE

OPEN ACCESS



Urban visual intelligence: Uncovering hidden city profiles with street view images

Zhuangyuan Fan<sup>a</sup>, Fan Zhang<sup>b,1</sup>, Becky P. Y. Loo<sup>a,c</sup>, and Carlo Ratti<sup>d</sup>

Edited by Richard Shearmur, McGraw-Hill Education  
 Member Susan Hanson

A longstanding line of research has shown that the visual appearance of a neighborhood can be a strong predictor of its socioeconomic status. In this paper, we address the question of how to automatically estimate the socioeconomic profiles of neighborhoods from street view images. We propose a deep learning-based approach that automatically detects and classifies urban features such as street furniture, building styles, and vegetation. Our method significantly outperforms traditional methods in terms of accuracy and scalability. Our findings suggest that street view imagery can be a valuable tool for understanding the socioeconomic profiles of neighborhoods and for informing urban planning and policy-making.

Paper Session 4: Finding your Way (to this session)

ASSETS '19, October 28–30, 2019, Pittsburgh, PA, USA

Deep Learning for Automatically Detecting Sidewalk Accessibility Problems Using Streetscape Imagery

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ABSTRACT

Recent work has applied machine learning methods to automatically find and/or assess pedestrian infrastructure in online map imagery (e.g., satellite photos, streetscape panoramas). While promising, these methods have been limited by two interrelated issues: small training sets and the choice of machine learning model. In this paper, aided by the recently released Project Sidewalk dataset of 300,000+ image-based sidewalk accessibility labels, we present the first examination of deep learning to automatically assess sidewalks in Google Street View (GSV) panoramas. Specifically, we investigate two application areas: automatically validating crowdsourced labels and automatically labeling sidewalk accessibility issues. For both tasks, we introduce a novel deep learning architecture (FastNet) modified to support image and image-text (e.g., textual features (e.g., geography)). We present an analysis of performance, the effect of our non-image features and training set size, and cross-city generalizability. Our results significantly improve on previous methods and, as a result, we believe our work will be a valuable resource for researchers and practitioners alike.

Author Keywords

Neural networks, computer vision, accessibility, sidewalks, curb ramps, Google Streetview

and infrequent. <sup>1</sup> Moreover, the resulting data is in disparate formats, is not typically open (i.e., published online), and is not intended for end-user tools [23, 50]. To expand who can collect sidewalk data and to improve data granularity and freshness, researchers have introduced smartphone-based tools [15, 46, 52] as well as instrumented wheelchairs [35, 39, 51, 57], both of which capture sidewalk information *in situ* as it's experienced. However, these tools have been limited by low adoption, small geographic coverage, and high user burden (e.g., requiring users to take out their phones, load an app, take a picture, annotate it, and upload it) [20, 23].

To partially address these scalability issues, researchers have begun developing automated methods for sidewalk assessment using machine learning and computer vision on satellite photos [11, 33, 34, 36, 37, 38, 40, 41, 42, 43, 44, 45, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 58, 59]. While still early, these complementary approaches promise to dramatically decrease manual labor and cost. However, they have been limited by two interrelated issues: small training sets and the choice of machine learning model [11, 33, 34, 36, 37, 38, 40, 41, 42, 43, 44, 45, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 58, 59]. We present the first examination of deep learning methods to automatically assess sidewalk accessibility in terms of curb

We present the first examination of deep learning methods to automatically assess sidewalk accessibility in terms of curb

COMMENT | 13 August 2023

# Putting Africa on the map

**A lack of street view imagery in many countries mean valuable data isn't available to researchers.**

By [Mette Bendixen](#), [Tawanda Kanhema](#) & [Lars L. Iversen](#)

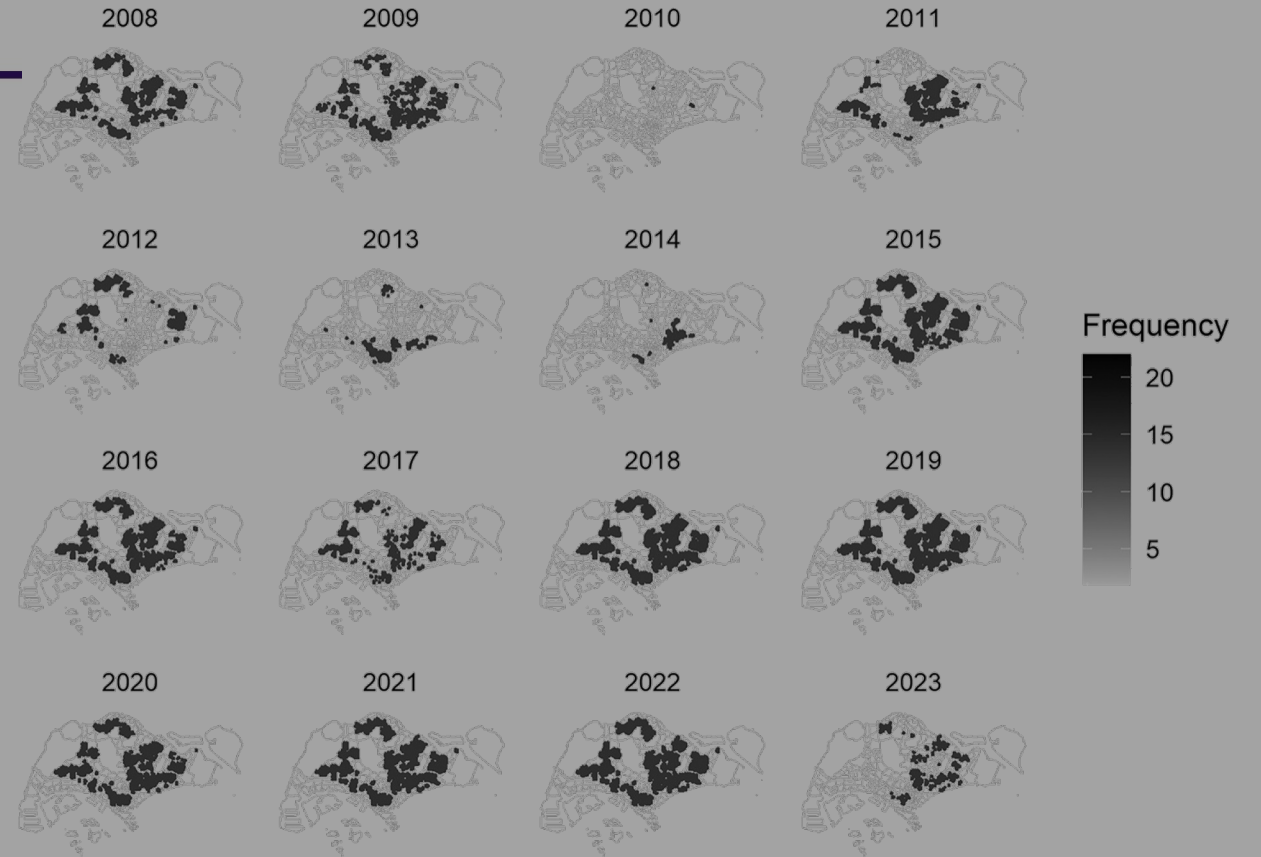


a



**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.**

The spatio-temporal distribution of images retrieved from Google Street View in Singapore

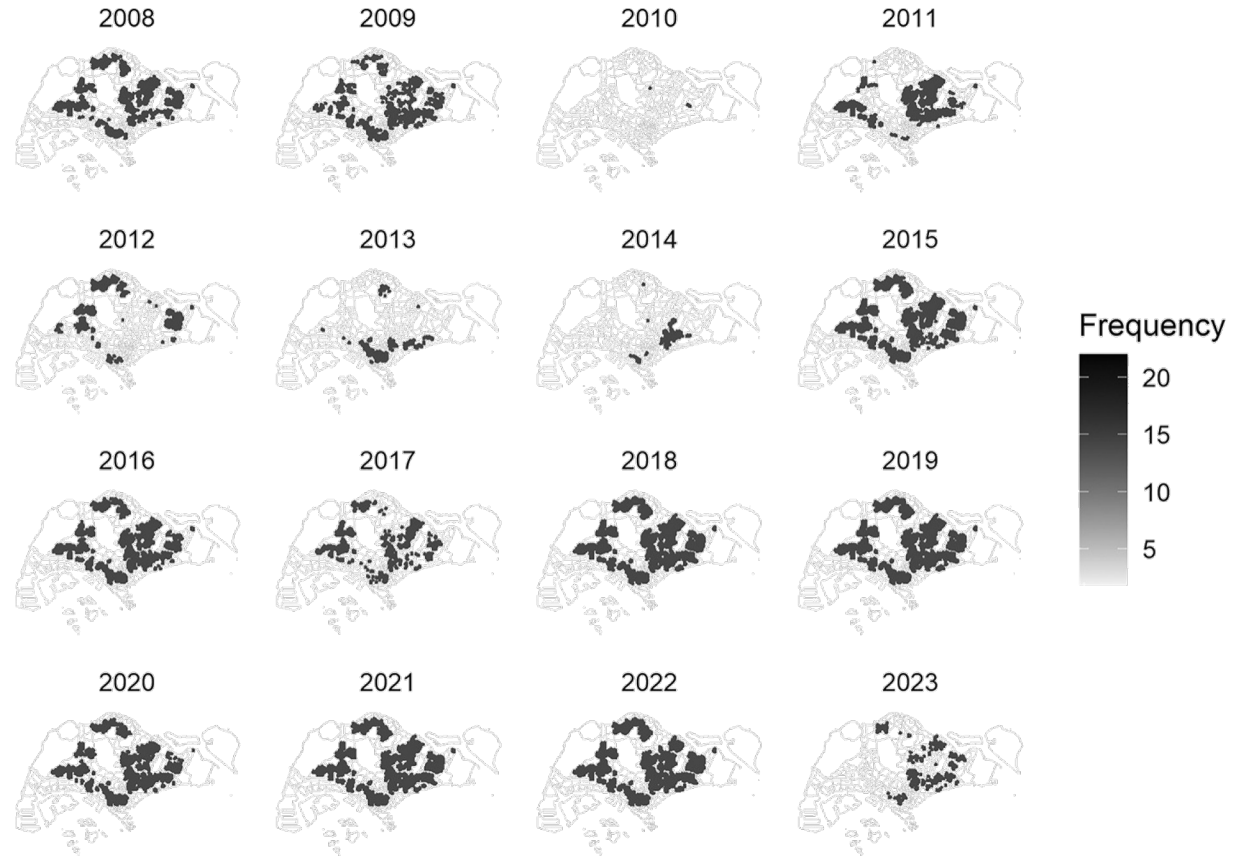


Source: Wang, Z., Ito, K., & Biljecki, F. (2024). Assessing the equity and evolution of urban visual perceptual quality with time series street view imagery. *Cities*, 145, 104704.

Such disparities may reflect deeper inequalities in the digital representation of urban spaces, potentially biasing downstream analyses and influencing policy decisions.



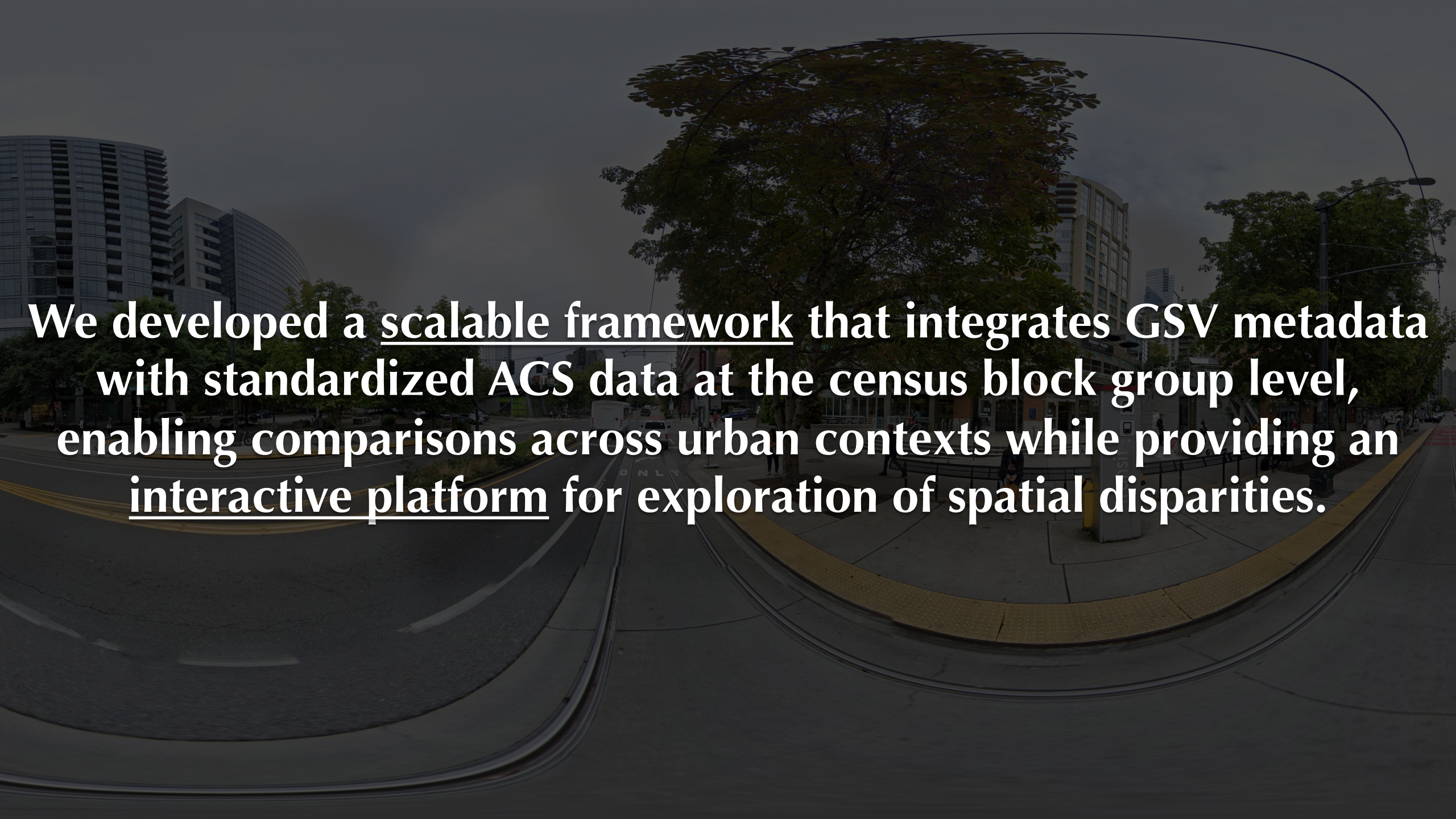
The spatio-temporal distribution of images retrieved from Google Street View in Singapore



Source: Wang, Z., Ito, K., & Biljecki, F. (2024). Assessing the equity and evolution of urban visual perceptual quality with time series street view imagery. *Cities*, 145, 104704.

# Gaps

- Lack scalable and reproducible frameworks for integrating standardized demographic data with SVI metadata.
- Most analyses are limited to specific cities or regions, preventing broader geographic comparisons.
- Lacks accessible, interactive tools for transparent exploration of spatial representation patterns.

A wide-angle, fisheye view of a city street intersection. The scene is captured from a low angle, looking down the street. On the left, a modern, curved building with a glass facade is visible. In the center, a large, leafy tree stands on the sidewalk. To the right, another modern building is visible. The street is paved with asphalt and has yellow curb markings. The sky is overcast and grey. The overall image has a dark, muted color palette.

**We developed a scalable framework that integrates GSV metadata with standardized ACS data at the census block group level, enabling comparisons across urban contexts while providing an interactive platform for exploration of spatial disparities.**

# Pipeline



```
{bbox| min lat,  
max lat, min lon,  
max lon}
```

City Bounding  
Box (OSM)

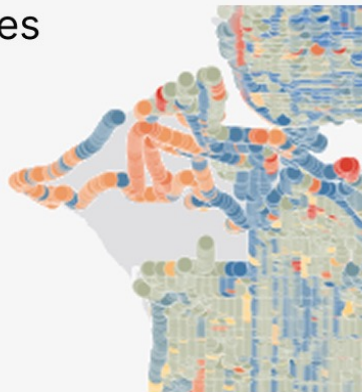


Queries



Google Maps

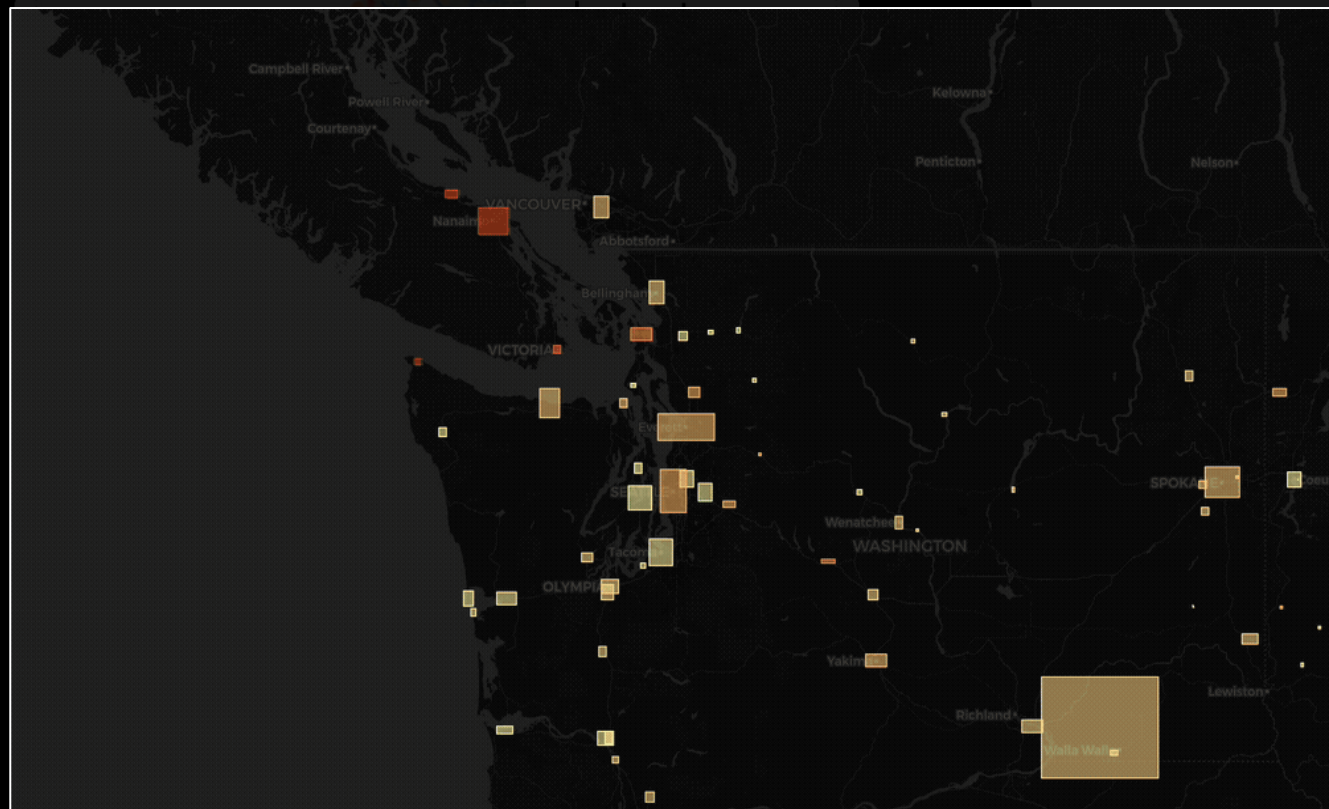
Street View  
Static API



Latest available  
GSV metadata

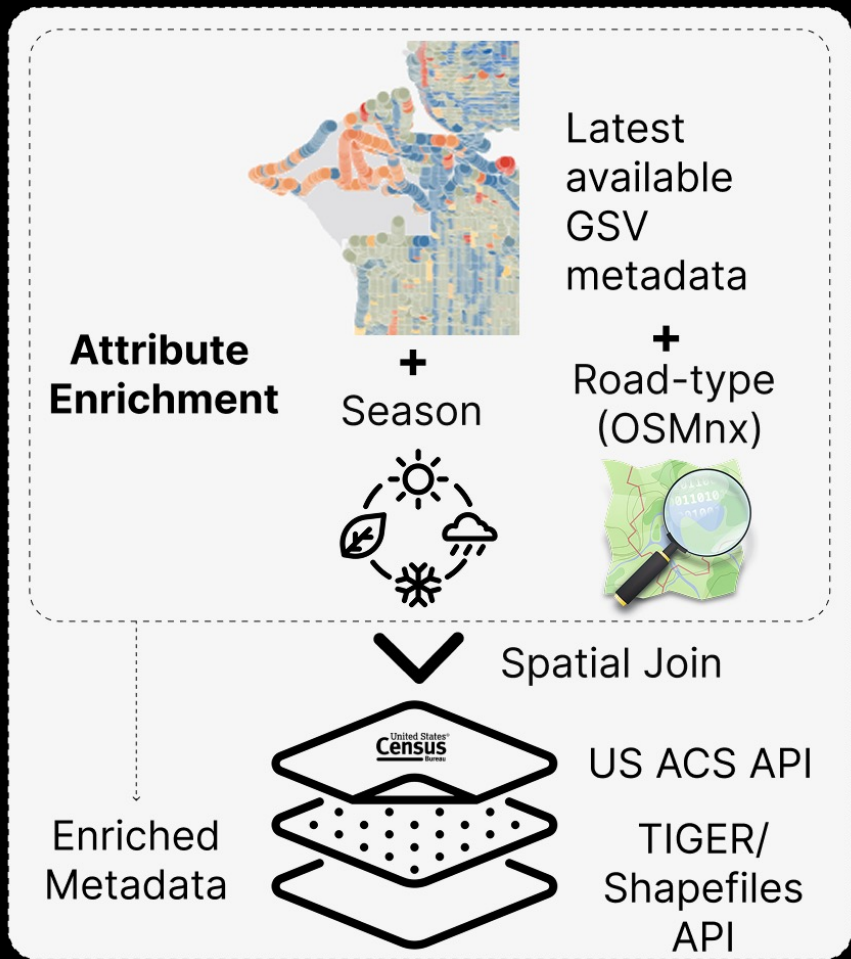
**GSVTracker &  
Downloader**

## Bounding Boxes

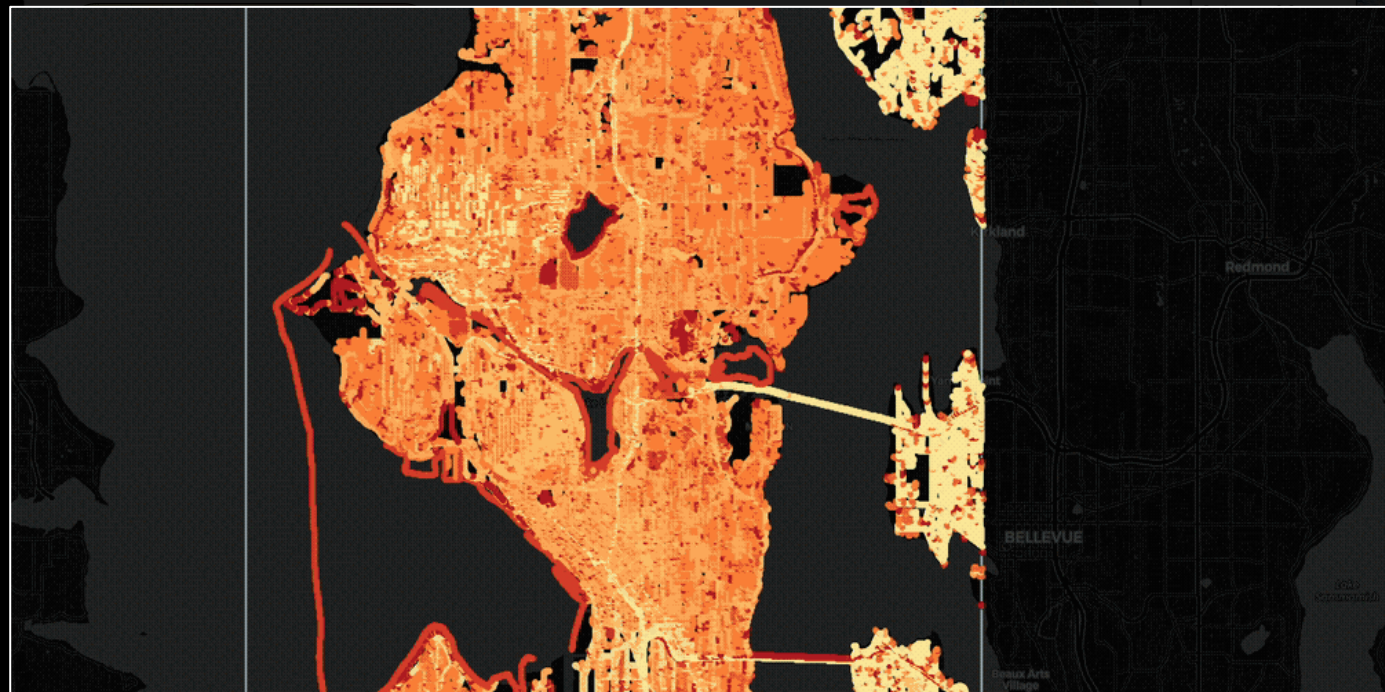


**GSVantage**  
Interactive Tool

# Pipeline



## GSV Metadata

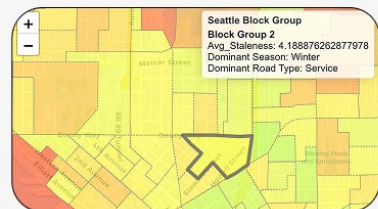


Functions

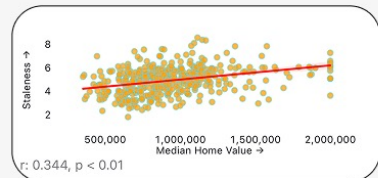
Spatial Distribution of Image Staleness: Sea

# Pipeline

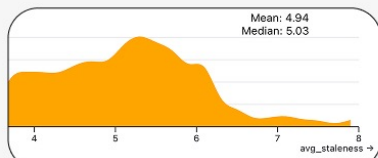
**GSVantage**  
Interactive Tool



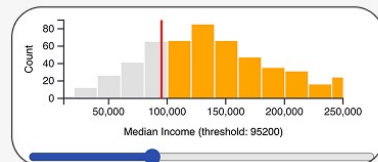
Interactive  
Mapping



Correlation  
Analysis

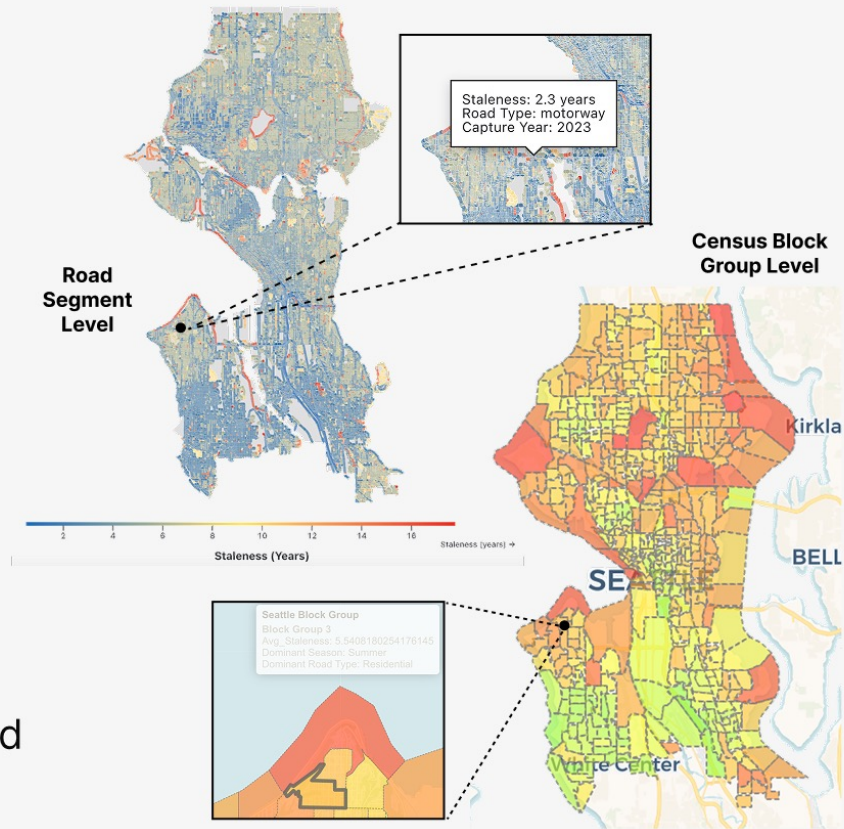


Staleness  
Distribution



Neighborhood  
Filtering

**Functions**



**Spatial Distribution of Image Staleness: Seattle Case**

**Correlation Analysis &  
Visual Analytics Dashboard**

# Demo

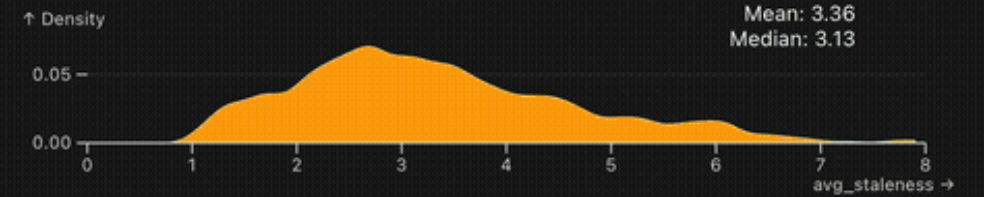
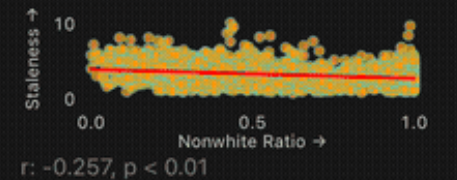
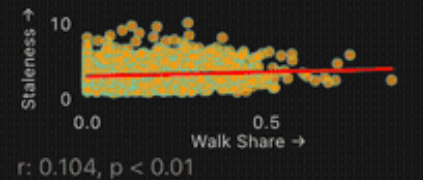
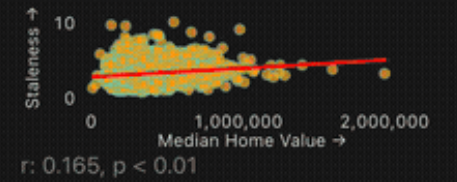
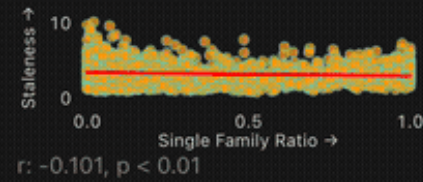
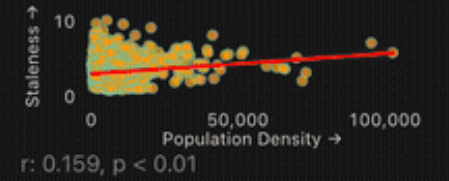
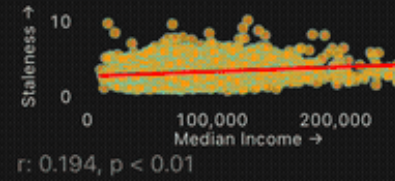
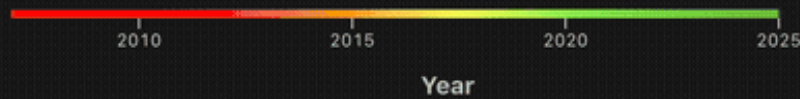
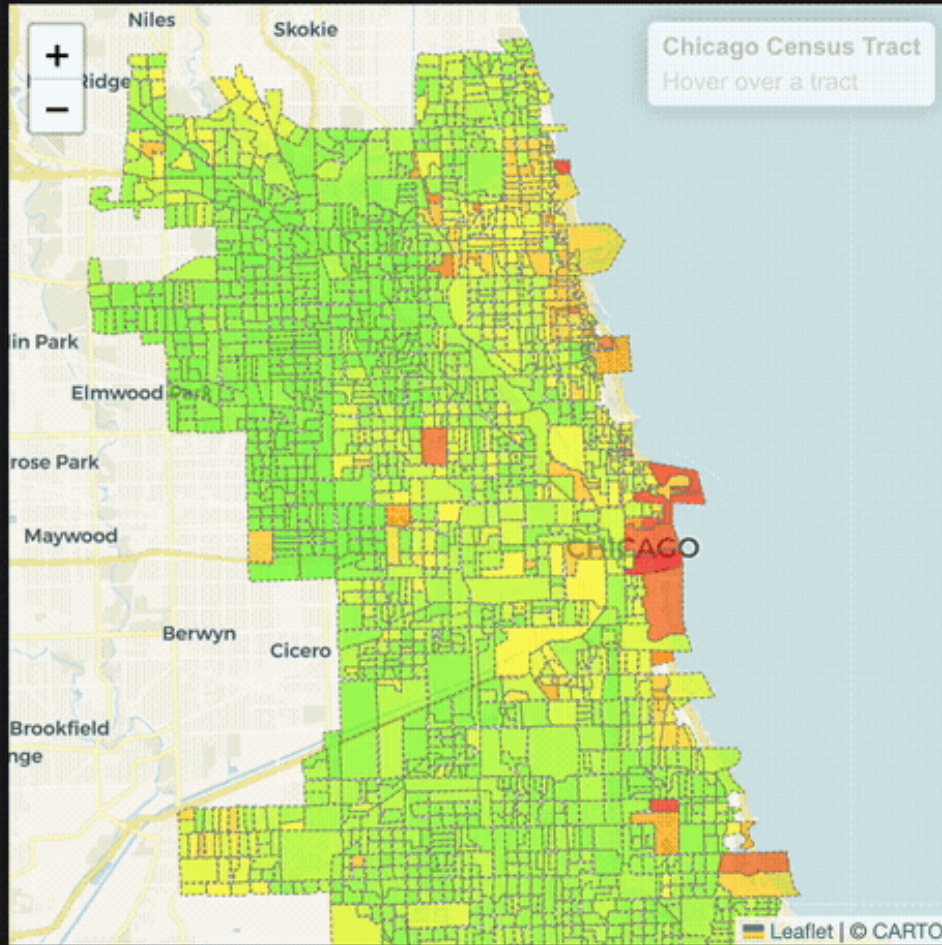


Home ←

- Atlanta
- Chicago
- Detroit
- Seattle

# Demo

## Chicago

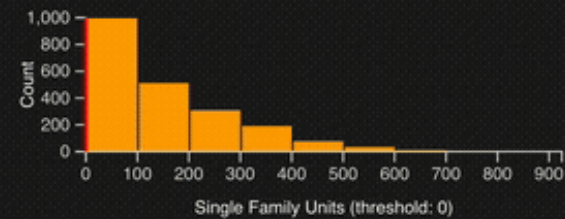
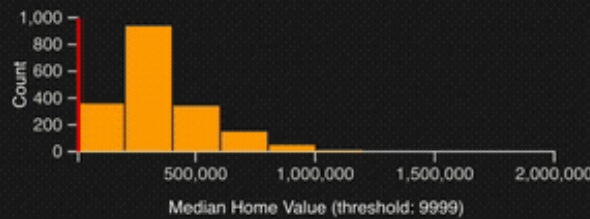
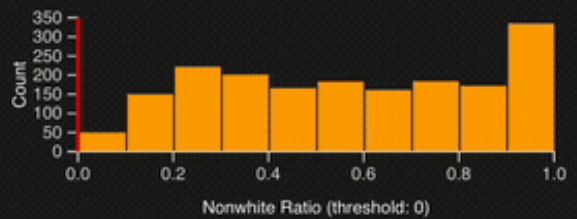
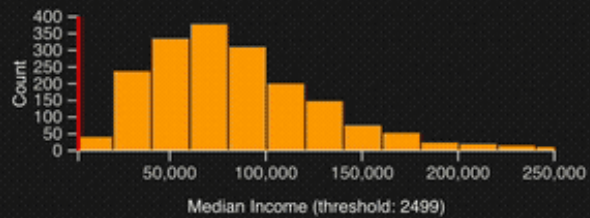
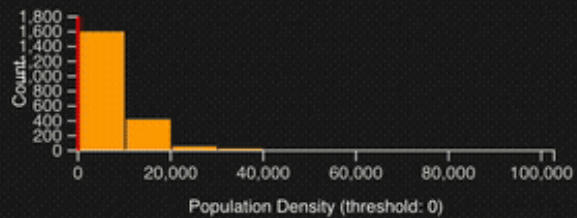


# Demo

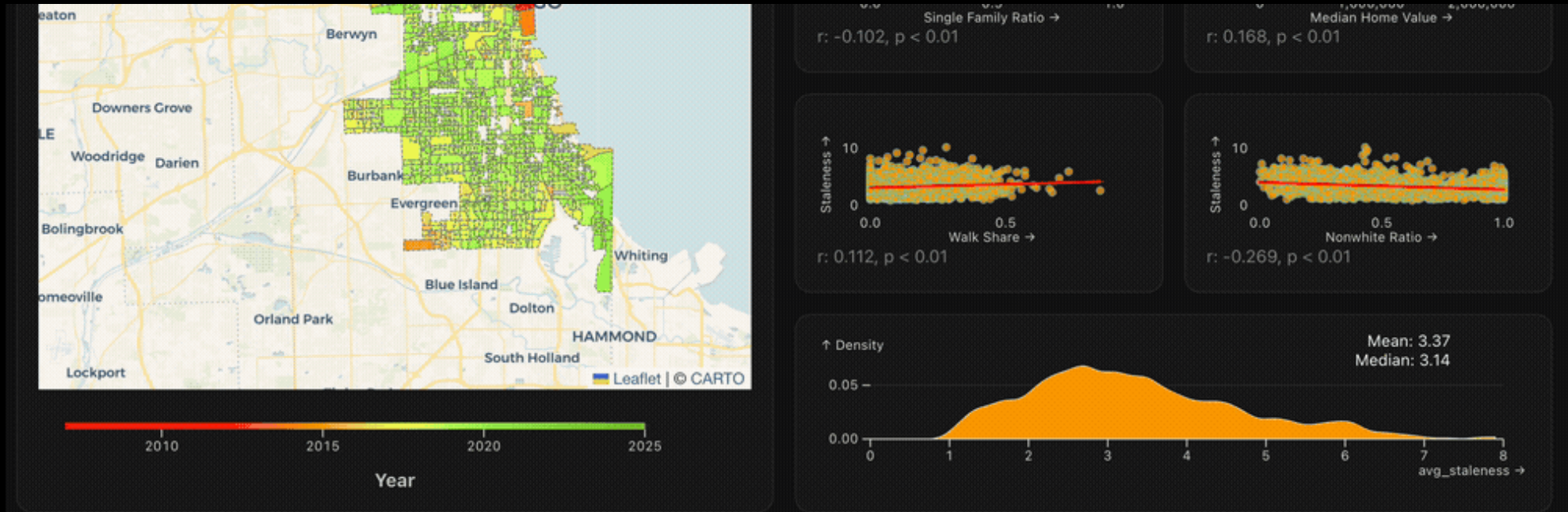
## Select your targeted neighbourhood

Use the filters below to explore how Google Street View image freshness varies by neighborhood characteristics.

Example: I want to see the distribution of image staleness in high-income neighbourhood.



# Demo

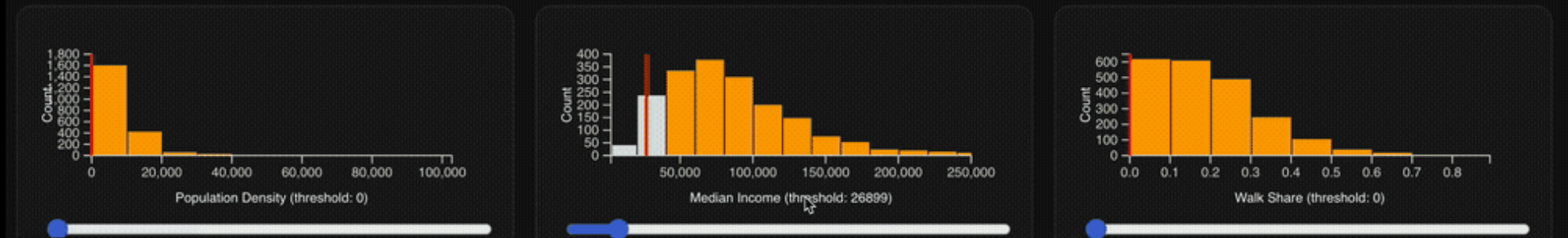


Reset All Filters

## Select your targeted neighbourhood

Use the filters below to explore how Google Street View image freshness varies by neighborhood characteristics.

Example: I want to see the distribution of image staleness in high-income neighbourhood.

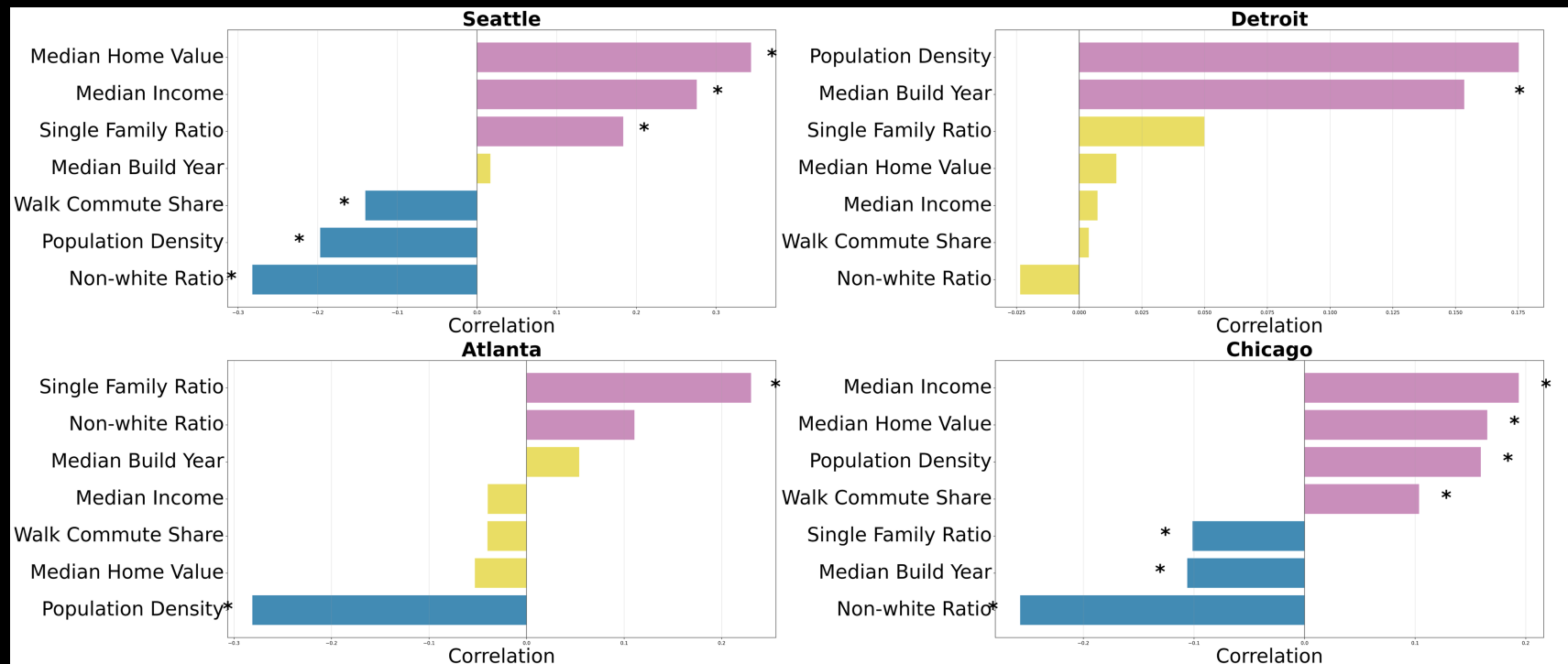


# Initial Results: Are GSV updates spatially equitable?

Sufficient observations (N) |  $N_{\text{Atlanta}} = 425$ ,  $N_{\text{Chicago}} = 2142$ ,  $N_{\text{Detroit}} = 622$ ,  $N_{\text{Seattle}} = 537$

## Consistent trends (Seattle, Chicago, Atlanta):

- $\uparrow$  Median Income / Home Value / Single-Family Ratio  $\rightarrow$  **Older imagery**
- $\uparrow$  Population Density / Walk Commute Share / Non-white Ratio  $\rightarrow$  **Fresher imagery**
- **Walk Commute Share** = most consistent predictor ( $r \approx -0.2$  to  $-0.3$ )
- Detroit = weaker / mixed results



# Initial Results

We observed a generally consistent “Digital Redlining” pattern in Google’s SVI update frequency.

Neighborhoods that are higher-income, higher-value, pre-dominantly single-family, or suburban tend to exhibit higher image staleness;

while denser, pedestrian-oriented, and higher-minority communities receive more regular updates.



# Contributions

- Empirical evidence of spatial inequalities in widely used street-level imagery.
- An open-source extensible framework for integrating imagery, metadata with social economic data across diverse contexts.
- An interactive visualization tool that promotes transparency and supports audits of digital equity.

# Limitations

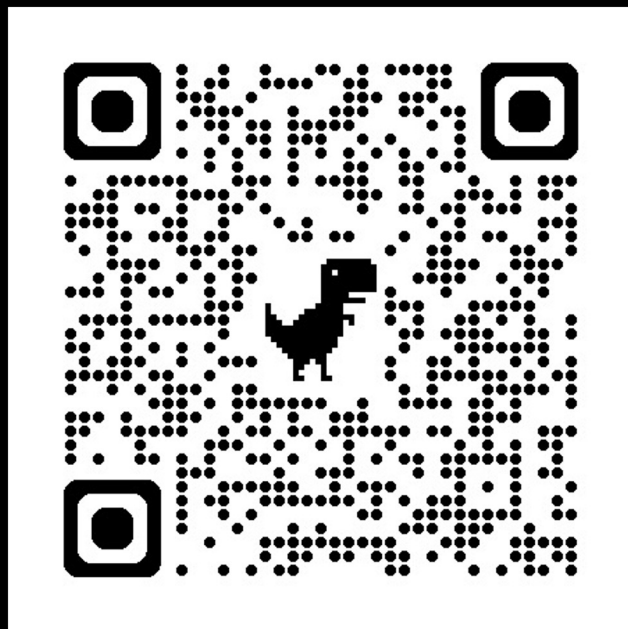
→ Spatial dependencies need further modeling.

→ There may be selection bias in the choice of cities; including more cities would improve generalizability.

→ Correlation  $\neq$  causation.

# Thank you

## Project Repo



[github.com/makeabilitylab/GSVantage](https://github.com/makeabilitylab/GSVantage)

## Let's Connect 🙋



LinkedIn



Google Scholar



Makeability Lab

# Street View for Whom?

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

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