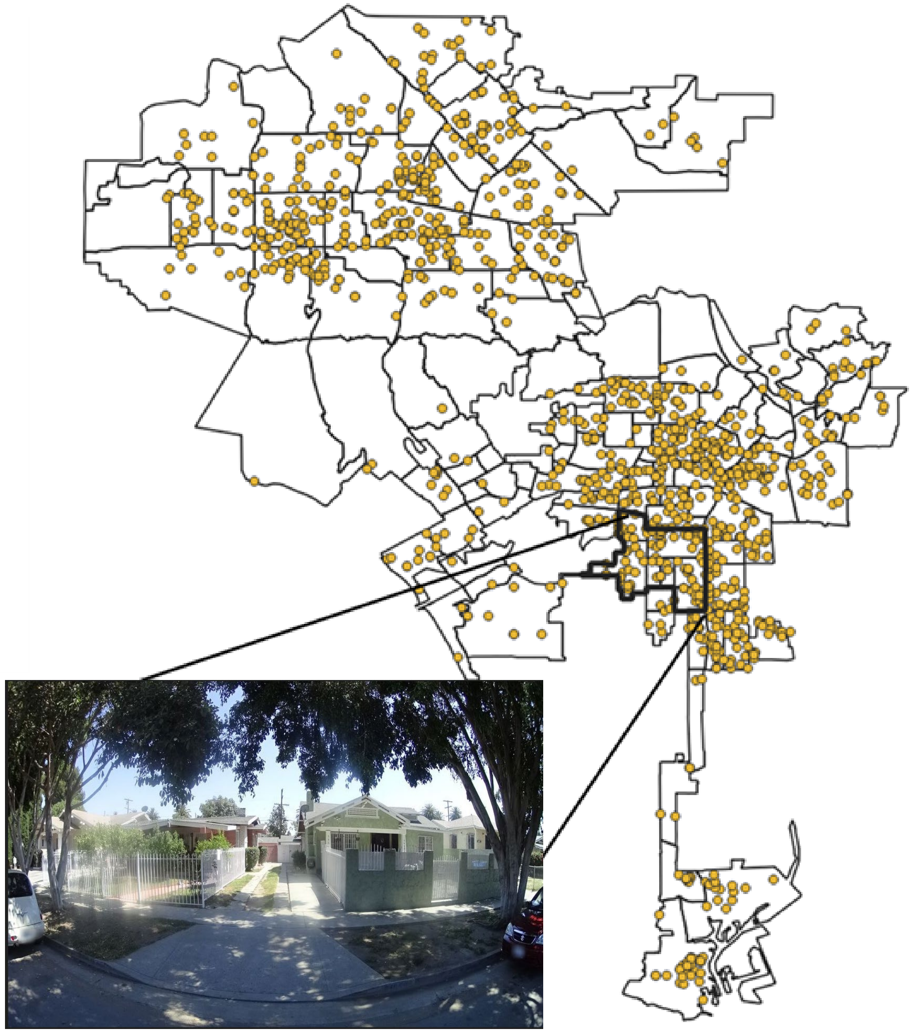
Integrating AI, Deep Learning, and Spatial Analytics to Investigate Environmental Correlates of Child Neglect

A Novel Integration of Social, Perceptual and Built Environmental Data to Predict Child Neglect Risk in Los Angeles, California

Gia Elise Barboza-Salerno, MA, MS, JD, PhD
Colleges of Social Work and Public Health
The Ohio State University
Creator: Investigating Spatial Structures in Urban Environments (ISSUES) lab
barboza-salerno.1@osu.edu

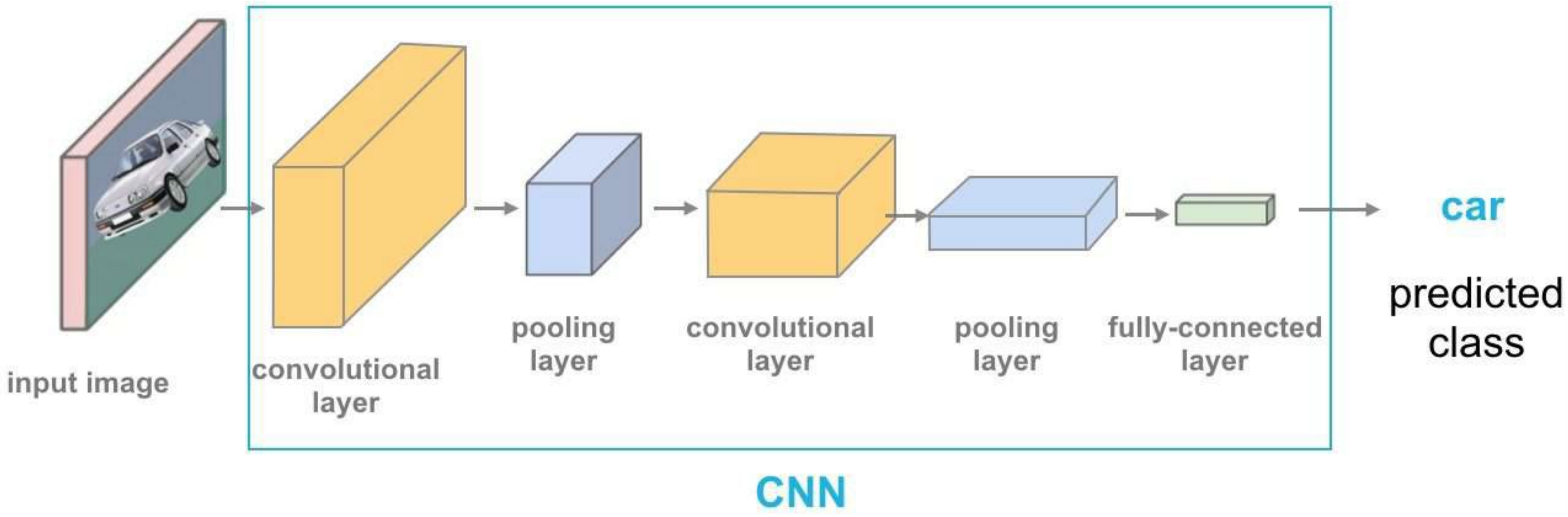
From Streets to Statutes: How Urban Environments Shape Neglect Risk

- Child neglect is a **public health** and **civil rights** crisis
- **Legal Context**
  - California WIC § 300(b)(1): Neglect is the failure of a parent or guardian to provide adequate food, clothing, shelter, or supervision, placing a child at risk of serious harm.
- **Why 'Place' Matters**
  - Neglect is not solely the result of individual or family circumstances.
  - Risk is shaped by the neighborhoods where families live.
  - Environmental conditions — housing quality, access to services, exposure to hazards — often align with the legal definitions of neglect.
- **The AI Advantage**
  - Connects objective measures (e.g., infrastructure, green space) with subjective impressions (e.g., safety, upkeep).
  - Produces a fuller picture of environments that may increase neglect risk.
  - Extends and strengthens research on place-based prevention and intervention.

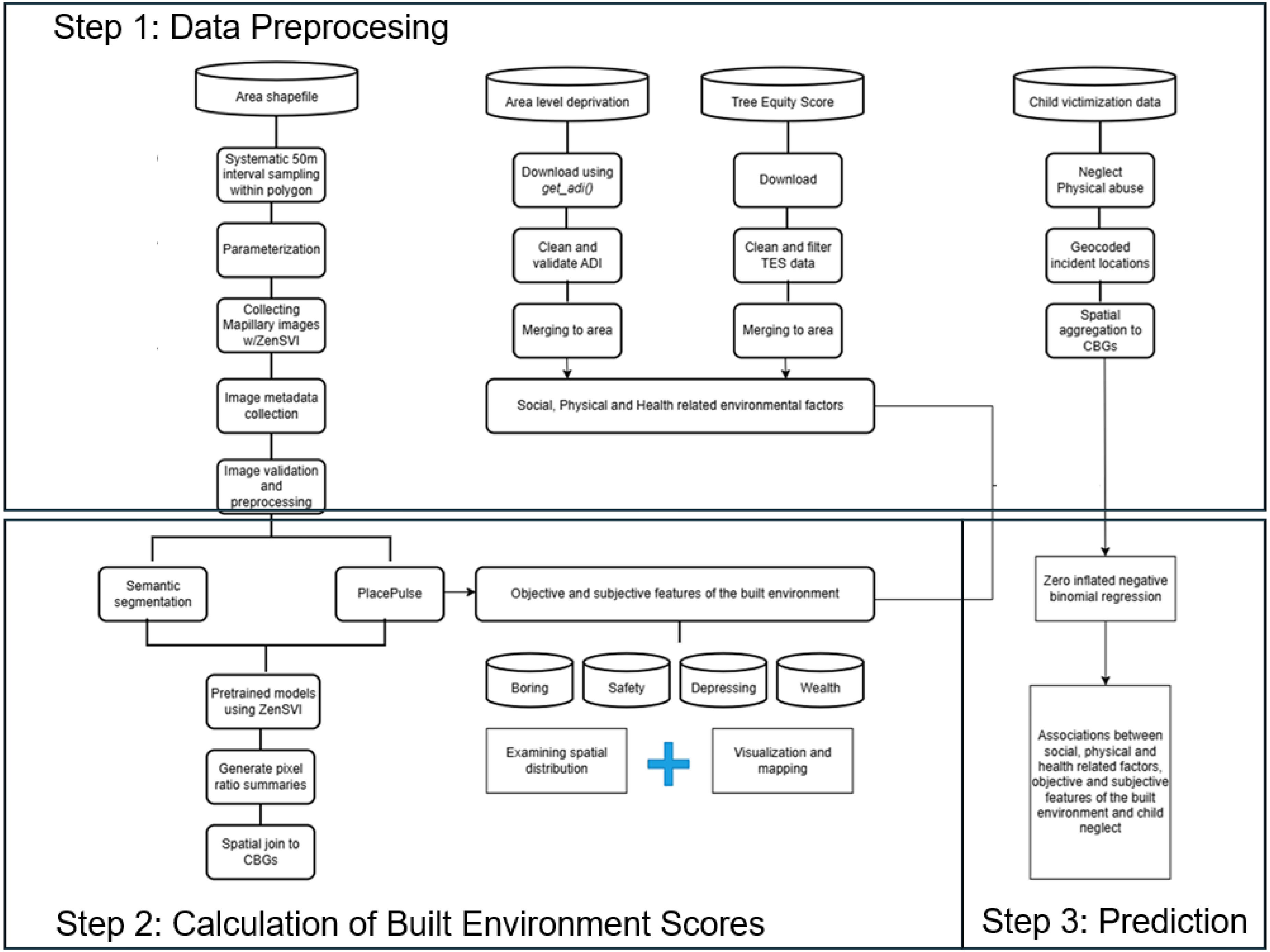


From Pixels to Neighborhood Patterns: How AI translates images into indicators

- AI uses computer vision models — powered by deep learning–based semantic segmentation — to teach computers how to 'look' at images. The system scans every pixel in a street-level photo, interprets what it sees, and labels each feature, pixel-by-pixel."
- Using AI-driven computer vision on street-level images, you can:
  - Measure the built environment (e.g., green space, building structures, and open areas)
  - Evaluate neighborhood infrastructure (e.g., sidewalks, roads, lighting, and public spaces)
  - Gauge local perceptions: *how do people evaluate the environment* (e.g., do they feel safe)*?*



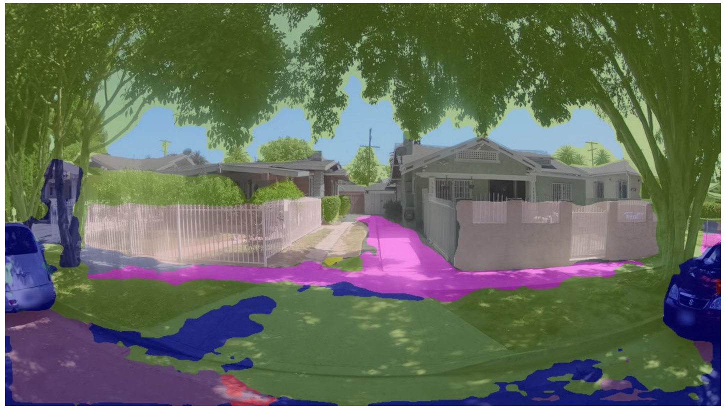
Connecting the Built Environment and Perceptions of Place to Neglect Risk



AI-driven Semantic Segmentation

Original Image

Street-level image showing
- Homes
- Vegetation
- Vehicles
- Sidewalks
- Roads



Segmentation Overlay

AI highlights each feature:
- Light Brown/Grey: Building façades
- Green: Vegetation
- Blue: Vehicles
- Pink/Purple: Sidewalks
- Dark Blue: Roads

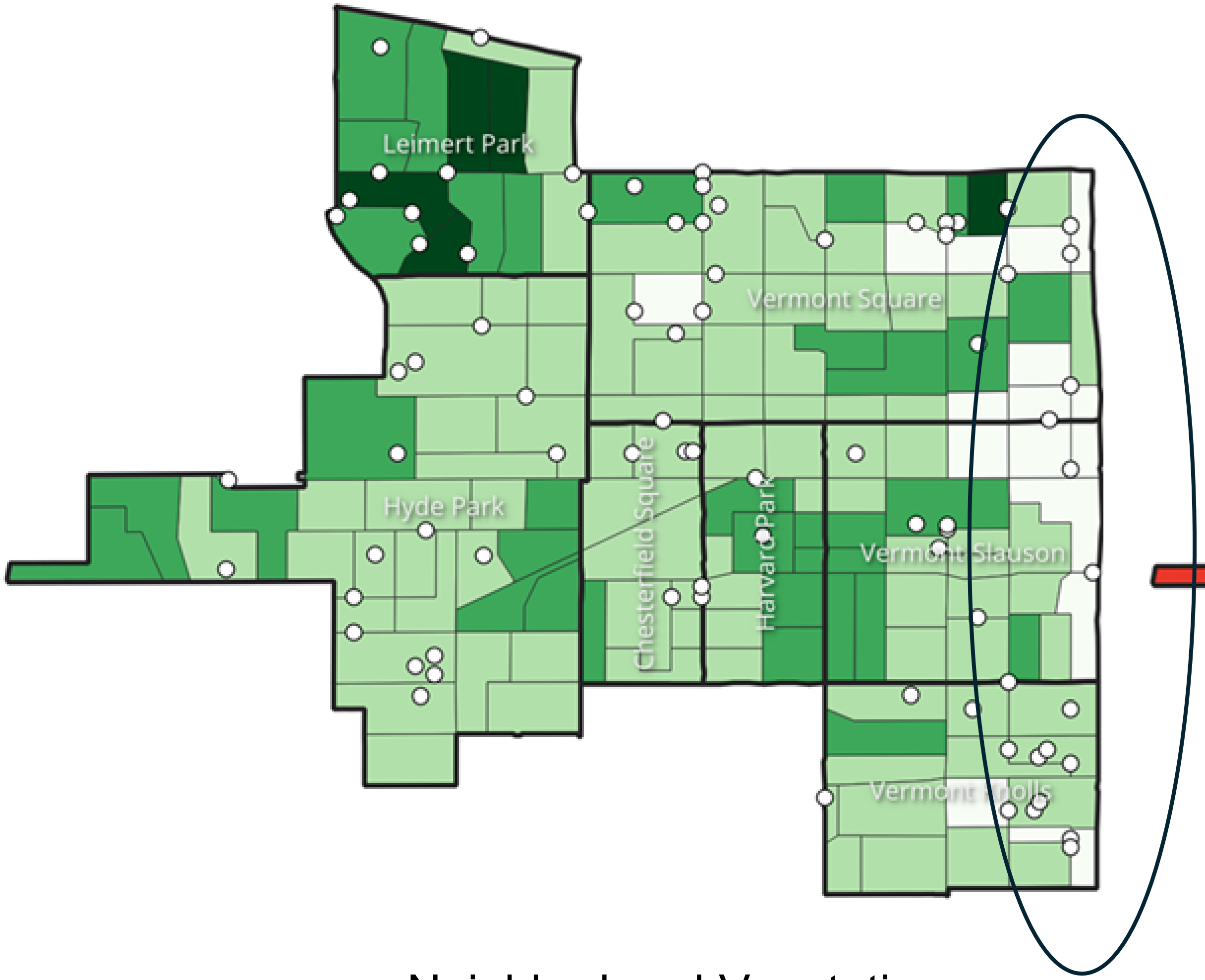
Segmentation Mask

AI segmentation detects the most common categories in each image
- 59.1% vegetation
- 9.64% fences
- 7.76% buildings
- 4.94% roads
- 4.31% sidewalks

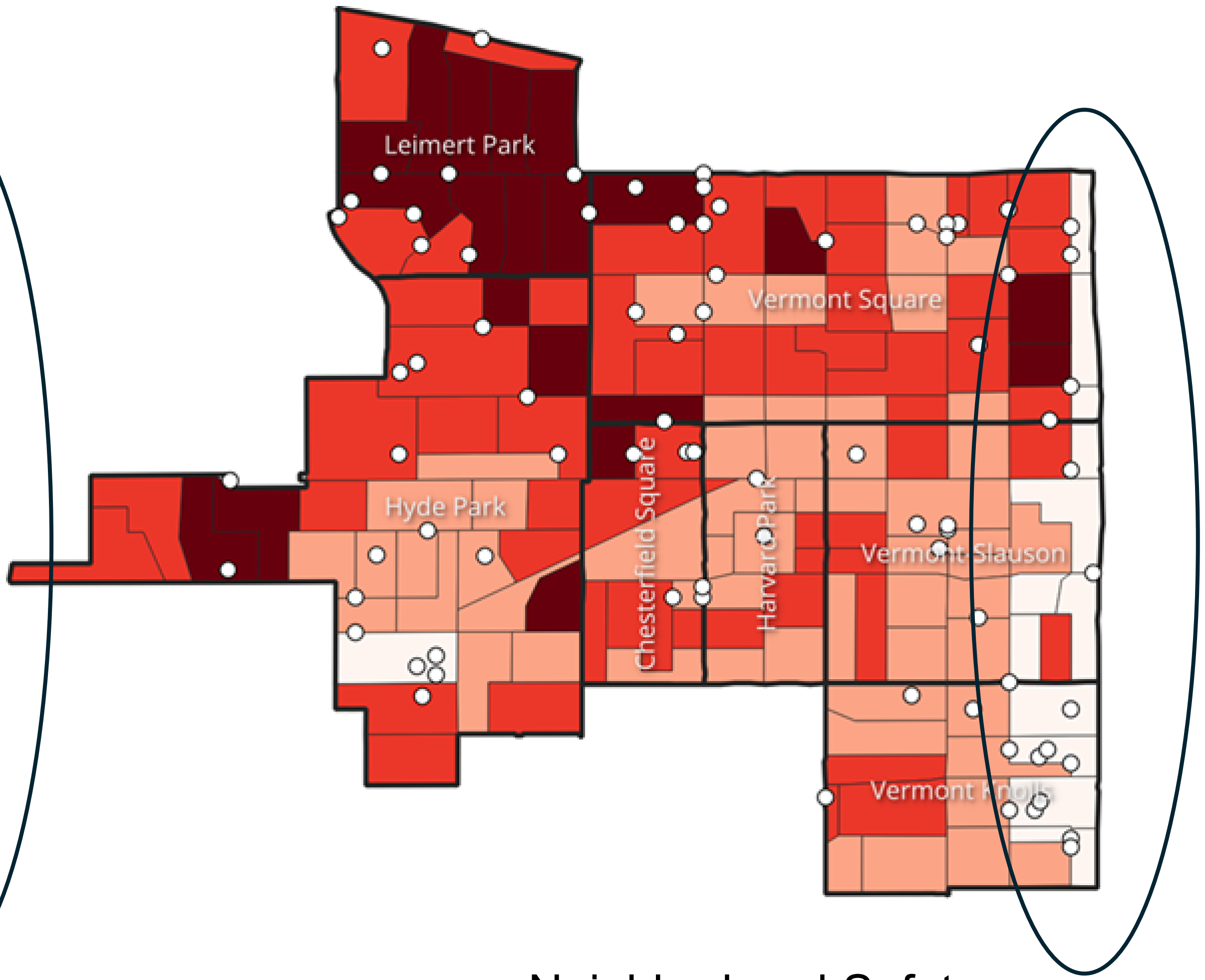
Add Perception Scores

- Classified images using deep learning models trained to recognize subjective impressions

The Spatial Distribution of the Built and Perceived Environment



Neighborhood Vegetation
(Objective Score Summary)



Neighborhood Safety
(Perception Score Summary)

Higher Social Deprivation = Lower Green Space and Safety Perceptions

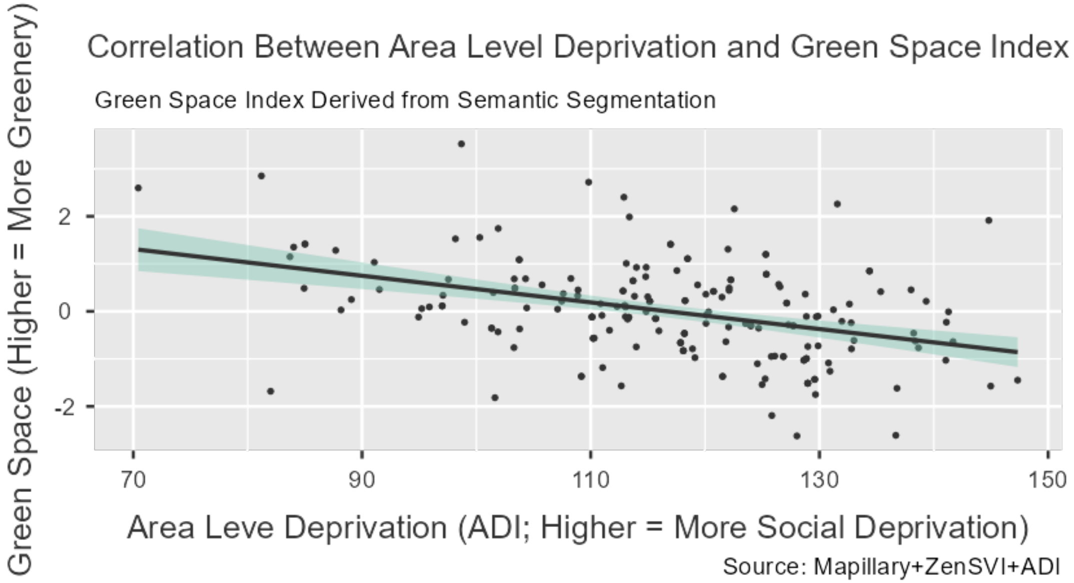


Figure 1. *Correlation between Area Level Deprivation and Green Space Index.* This scatterplot shows a negative association between the Area Deprivation Index (ADI; higher values indicate more social deprivation) and the Green Space Index (higher values indicate greater greenery at eye level).

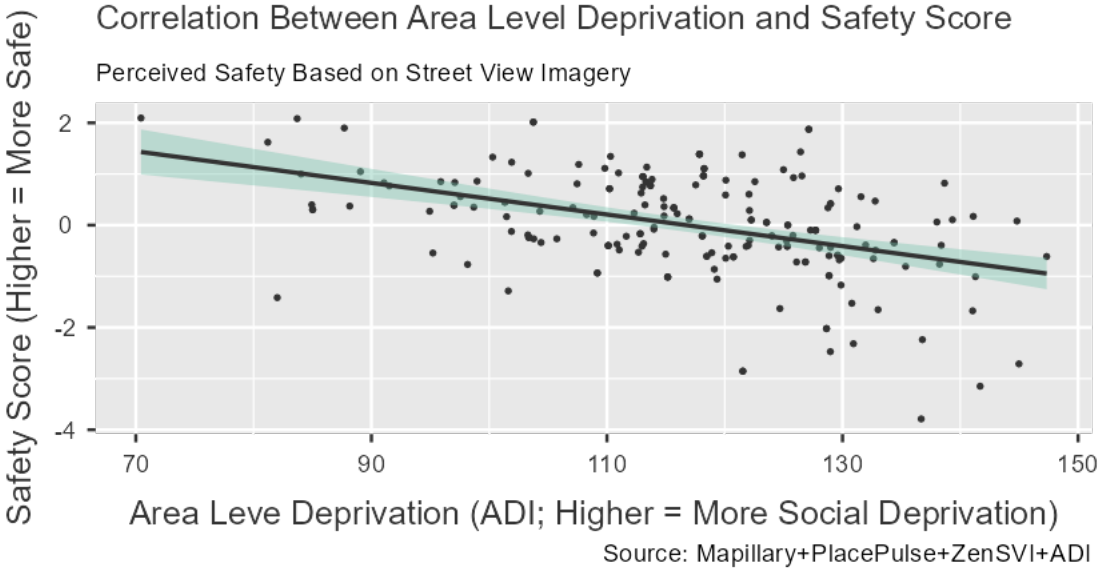


Figure 2. *Correlation between Area Level Deprivation and Safety Perception Score.* This scatterplot depicts the relationship between the ADI and perceived safety scores derived from AI-based perception models.

Neighborhoods facing greater social disadvantage tend to have both fewer environmental assets and lower safety perceptions — two factors that can compound neglect risk

Descriptive Links Between Environment, Perception, Social Deprivation, and Child Neglect Risk

Note: Higher score = greater values of the indicator

Variable	**Definition / Measures**	**Δ**	**Effect Size**
Green Space Index	Mean neighborhood score of vegetation cover, visible sky, and terrain, etc.	0.436	0.442
Surveillance Index	Mean neighborhood score of building frontage, fences, and walls, etc.	-0.121	-0.146
Land Use Mix Index	Mean neighborhood score of bicycles, buses, cars, motorcycles, pedestrians, riders, roads, sidewalks, trains, and trucks, etc.	0.200	0.269
Lighting Index	Mean neighborhood score of streetlights, traffic lights, poles, etc.	0.129	0.336
Safety Perception	Mean neighborhood perceived score for ‘safer’	0.249	0.255
Boring Score	Mean neighborhood perceived score for “boring”	0.0439	0.0446
Area Level Deprivation (ADI)	Area Deprivation Index	-9.478	-0.712

High-neglect areas tend to have less greenery, poorer built environment conditions, lower perceptions of safety, and much higher levels of social deprivation.

Policy Implications and Future Directions

- **Implications for child welfare systems**
  - Isolate factors associated with high risk: Identifies objective (e.g., green space, infrastructure) and subjective (e.g., safety perception) measures strongly associated with neglect risk.
  - Target high-risk locations: Spatial analysis shows exactly where — from individual sites to entire neighborhoods — environmental exposure risk is highest.
  - Evaluate for statutory alignment: Links California's legal criteria for neglect to measurable neighborhood conditions, guiding place-based prevention and intervention.
- **Other ISSUES lab applications using machine learning**
  - Structural Topic Models: Analyze narrative or text data (e.g., fatality reports, death records, police incidents) to detect spatial and thematic patterns.
  - Spatial Random Forest: Predict and map risk using environmental, social, and spatial features to detect the most important correlates of violence-related harm exposure.
  - Application of predictive analytics: Evaluate the conditions in which child welfare systems can use predictive analytics to prevent child harm (and when they cannot).

File Name	Measure	Unit of Analysis
pixel_ratios_wide.csv	Pixel-level proportion of each semantic segmentation class in a single image. pivoted to wide format — one row per image with each label as its own column.	Image-level
pixel_ratios_with_coords.csv	Pixel ratio data joined with lat/lon from mly_pids_renamed.csv.	Image-level with coordinates
mly_pids_renamed.csv	Mapillary photo IDs and coordinates for downloaded images with consistent column names for merging with segmentation output.	Image-level
combined_summaries_<indicator>_results.csv	Combined perception classification scores (e.g., “more depressing”) for all batches.	Image-level
summaries_<indicator>_map.geojson	Geospatial file mapping perception scores to coordinates.	Image-level with coordinates
image_metadata.csv	Image-level metadata from Mapillary (speed, heading, capture time, sequence).	Image-level
street_metadata.csv	Aggregated metadata per Mapillary sequence (street segment).	Street-segment level
grid_metadata.csv	Aggregated metadata by H3 hexagon grid.	Grid level

The code used to run this analysis is available on my lab’s GitHub website (in progress):
[issues-osu/ai-neglect]