Northeastern University
Solutions to Urban Pollution

MAPC MULTI-HAZARD

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Overview

Heat and Air Pollution are frequently expressed as separate aggregations up to the census tract or town average. However, there is significant variation within these aggregations, even between adjacent streets. These *microspatial inequities* were identified within Boston in a paper from O'Brien & Mueller (2023). The impetus of this project was to verify how these differences are expressed on a regional scale and use information about nearby infrastructure to identify drivers of heat and air pollution. Preliminary findings indicate that these microspatial inequities remain significant throughout the region, adding additional nuance to how we understand and address environmental hazards across a wider variety of community types.

Methods

Dependent Variables

- **Air pollution risk** is broken into 3 risk categories: **Low**, **Medium**, and **High (Fig 3)**
  - **Note**: In the model, risk is represented as a **binary** variable to indicate if the street is medium or high risk
  - **Risk** is **carbon monoxide emissions** combined with the street **Flushing Regime**
    - **Carbon monoxide emissions** are estimated using cell phone data from motor vehicles
    - **Flushing regime** refers to specific street **width to height ratios** that determine how well air circulates at the ground level
      - Height is estimated by **joining streets with their parcels** to get property data such as lot coverage and FAR **(Fig 1)**
      - Width is estimated by measuring the **distance** between **streets** and their **structures** on assigned parcels **(Fig 2)**
- **Heat** is represented as the average land surface temperature along the street segment **(Fig 4)**
  - Streets are broken into segments no more than 5 meters long and then the heat data is extracted onto it before being averaged

Air Pollution Correlates

- **Road type** including Local, Arterial, State Route, and Highway
- Binary variable indicating whether the street is a **dead end**
- Most common street level **land use**
- Neighborhood-level **land use clusters** to capture wider patterns of development
- **Population density** as people per square mile at the neighborhood level
- **Average floor area ratio (FAR)** at the neighborhood level

Heat Correlates

- Additional raster data from the urban heat island dataset including **albedo** (reflectiveness), **tree canopy**, and **impervious surface** percent
- Distance to the nearest body of **fresh water**
- Distance to the **ocean**

Street-Parcel Assignment

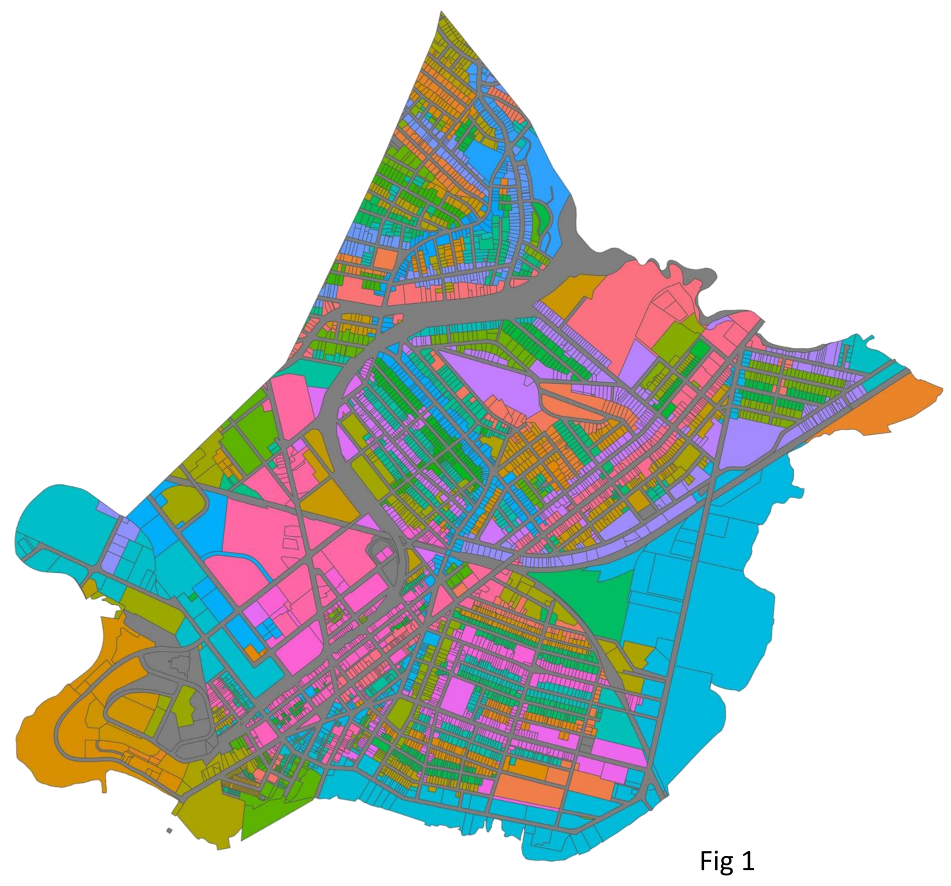

Fig 1

Street Width Calculation

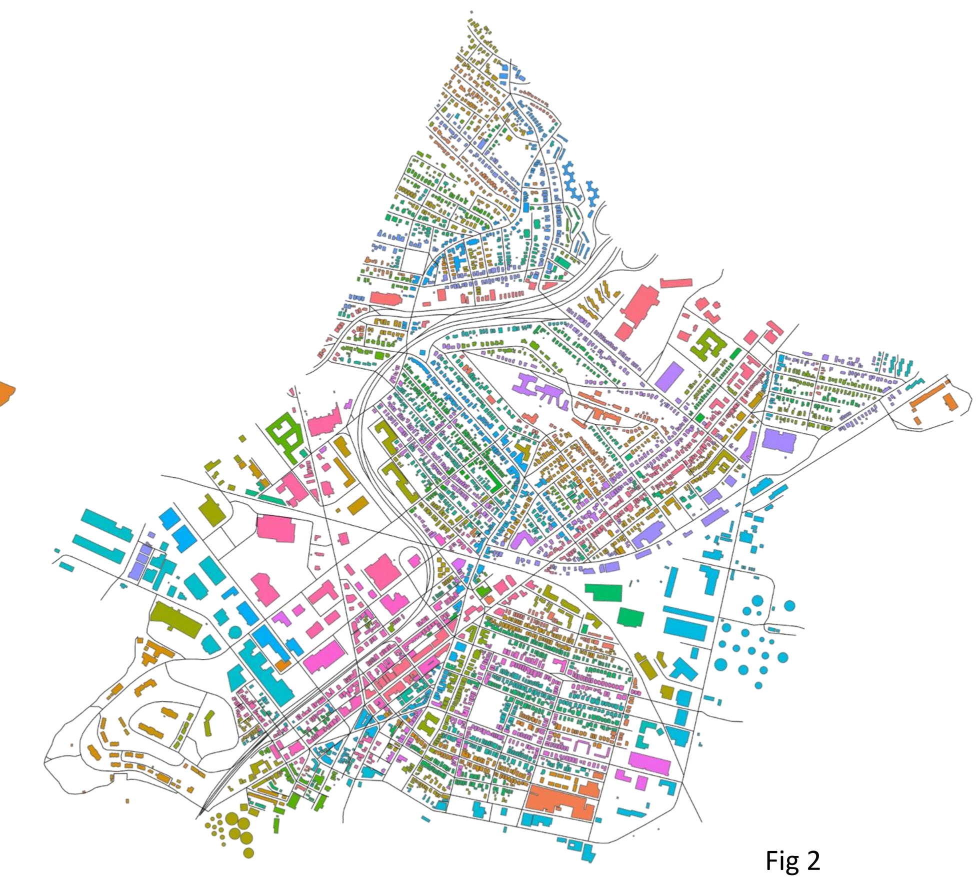

Fig 2

Air Pollution Risk Categorization

Fig 3

Temperature

Fig 4

Results

Air Pollution

- Neighborhood level data such as **land use clusters**, **population density**, and **average FAR** are most effective at explaining neighborhood and town level variation **(Tab 1)**
- **Air pollution** has a higher proportion of street-level variance, but the factors that were able to explain the most variance are found at the **neighborhood level** such as regional land use and population density
  - This contrasts O'Brien & Mueller (2023) which found huge explanatory power in street-level land use. This model instead is unable to explain any street-level variance but can explain some of the wider trends among neighborhoods and towns

Heat

- Unsurprisingly, **tree canopy** has the greatest impact on street heat, but **all factors** are significant out to the neighborhood level
- Street level characteristics alone explain over **70%** of the variance in temperature between both **towns** and **neighborhoods** and **60%** of street variance **(Tab 2)**
  - Adding neighborhood and town level characteristics continues to explain additional variance between neighborhoods and towns, but does not address any remaining street variance
- Differences between towns and neighborhoods are largely driven by **street-level characteristics**, meaning that similar types of streets tend to **cluster together** which drives the higher-level variance

Pollution Risk Models (Tab 1) R^2 of **0.43**

Factor Type	Town Explanation	Neighborhood Explanation	Street Explanation
Street Factors Only	4.696%	22.945%	-1.005%
Neighborhood Factors Added	62.164%	57.328%	-19.214%

Heat Models (Tab 2) R^2 of **0.86**

Factor Type	Town Explanation	Neighborhood Explanation	Street Explanation
Street Factors Only	71.493%	73.596%	59.801%
Neighborhood Factors Added	97.671%	89.238%	59.801%
Town Factors Added	97.139%	88.698%	59.802%

Hazards by Neighborhood

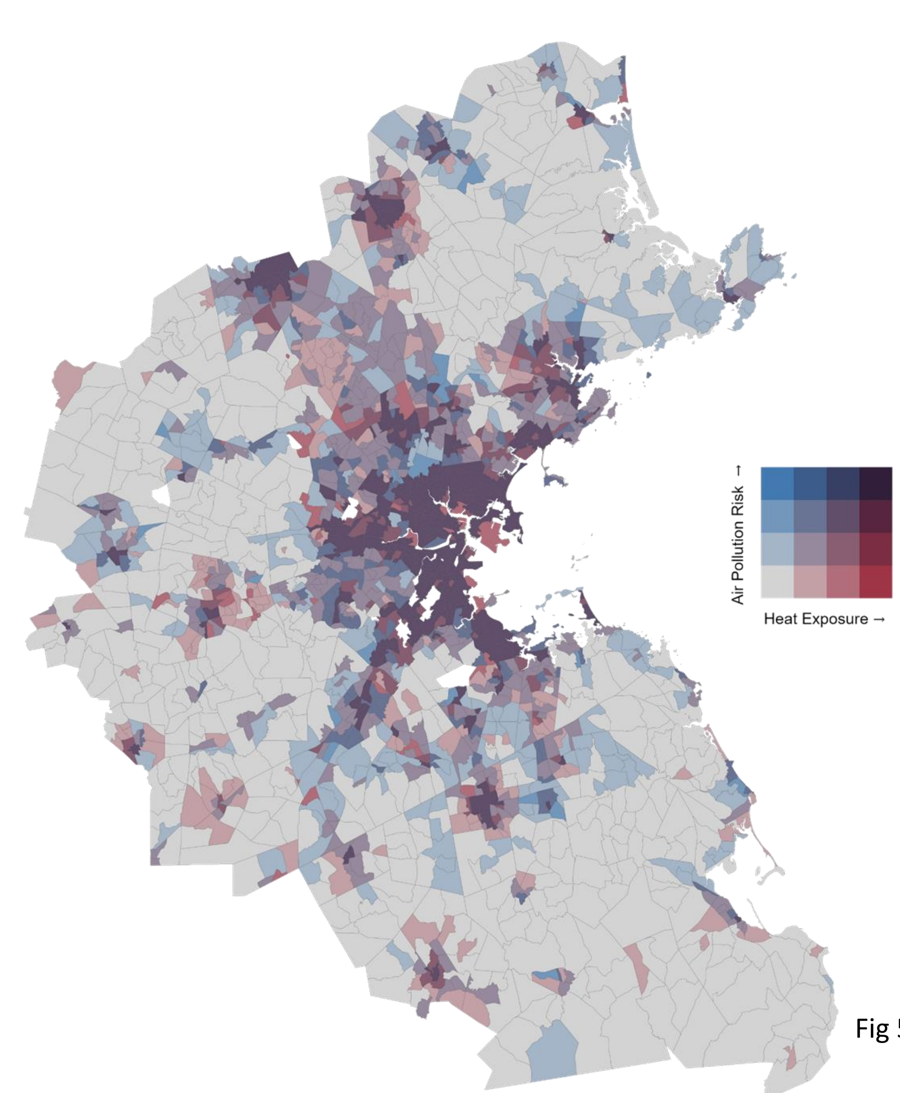

Fig 5

Discussion

Model Findings

- Microspatial inequities are certainly **not** an exclusively urban phenomenon, but the scale of differences throughout the region makes towns and neighborhoods serve as a greater source of variance, especially in air pollution
- Just under **50% of the air pollution variance** and just under **40% of the temperature variance** occurs **within neighborhoods**
- It's clear that local conditions have the greatest impact on hazard exposure
  - For **heat**, **street-level** infrastructure like **trees**, and **impervious surfaces** have the biggest impact, but streets still **influence each other,** as seen in the additional explanatory power from neighborhood characteristics
  - For **air pollution risk**, exposure is determined by traffic levels and the shape of the built environment
    - The greatest indicators of potential traffic levels like population and building density are not available at the street level, leading to no street-level explanation but modest neighborhood and town prediction

Multi-Hazard

- At the neighborhood level, heat and air pollution risk are correlated at **0.755 (Fig 5)**
  - Hazards are not correlated evenly across all towns, **Fig 6** shows the within-town correlation
- Most hazard research is done one hazard at a time, but the **combination** of **heat** and **air pollution** can be especially harmful (M. Stafoggia et al, 2023)
- There is also a significant **negative correlation** between **muti-hazard exposure** and **median income**, indicating that exposure is generally **regressive** in the region **(Fig 7)**

Hazard Correlation

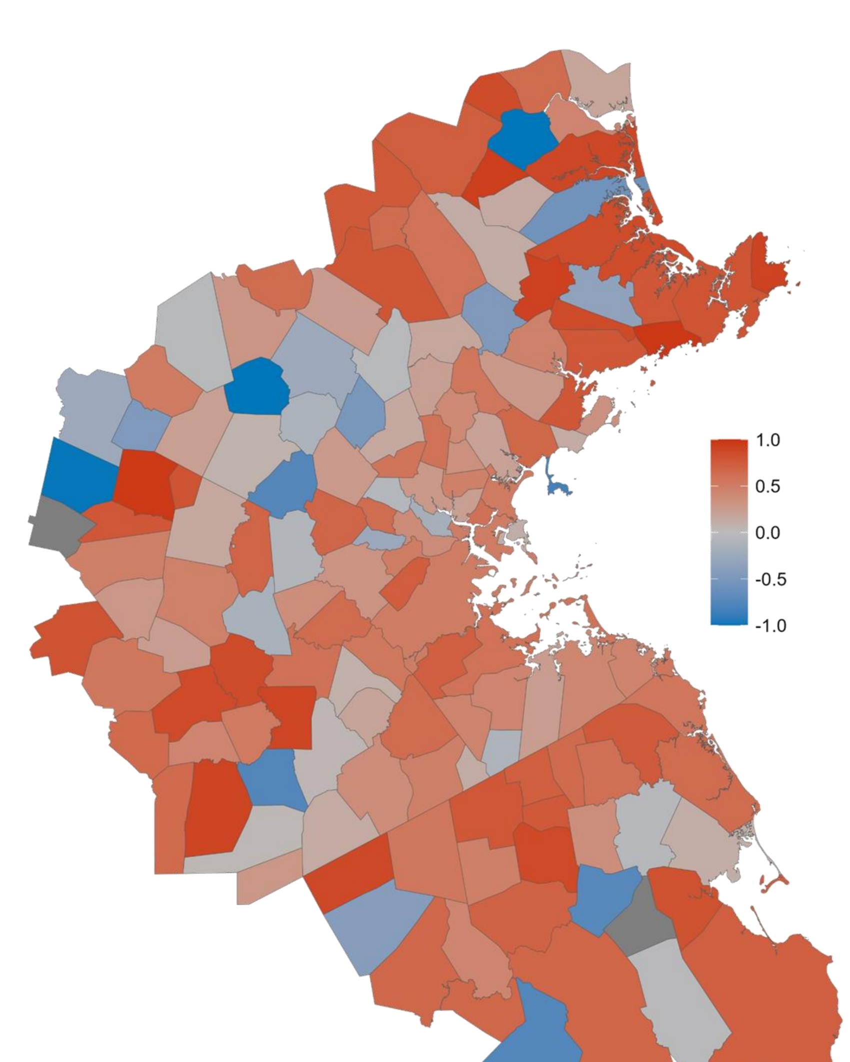

Fig 6

Income & Hazard Correlation

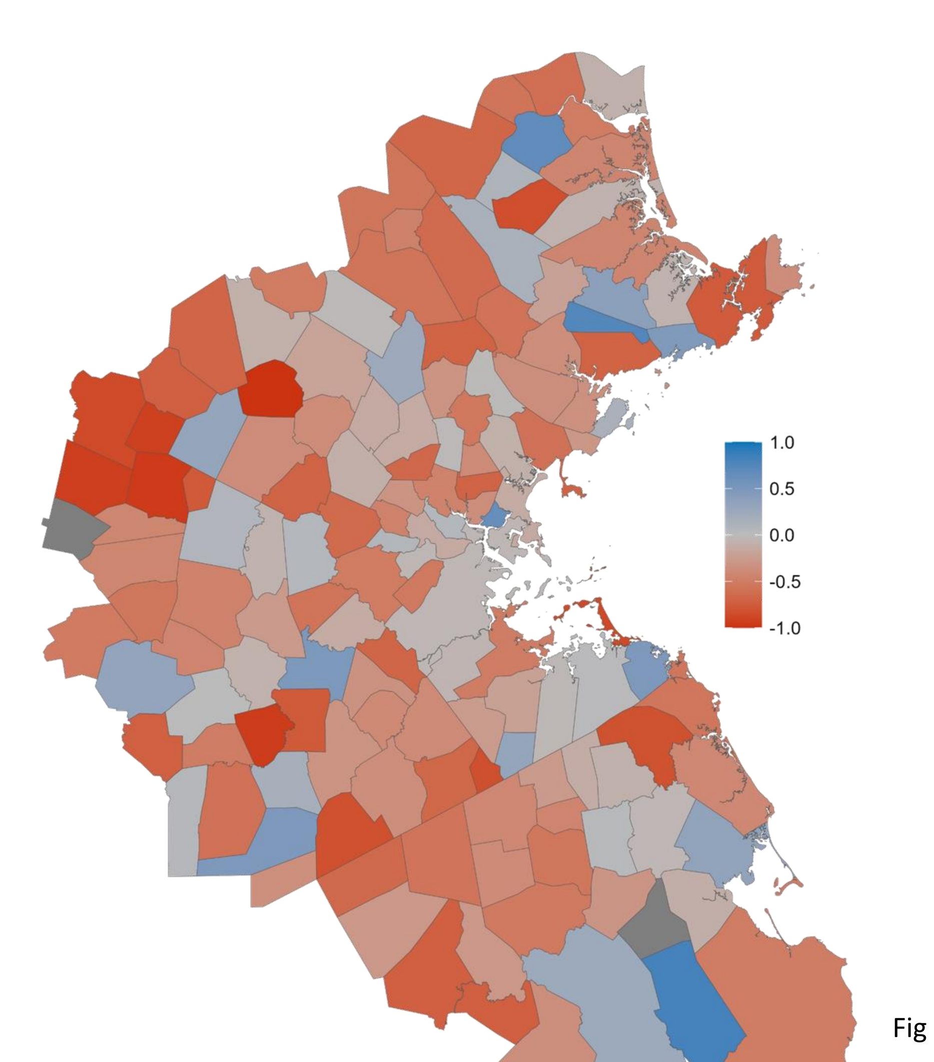

Fig 7

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