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Greening the Gap: Examining Urban Greenery in Shrinking Cities

- A case of Pittsburgh City

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Speaker intro

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What’s Shrinking Cities?

Urban shrinkage a significant **decline** in a city’s population

- Economic decline
- Increased poverty and inequity
- Strain on infrastructure and services
- Environmental concerns

Urban shrinkage is becoming increasingly **common**

- 5,004 shrinking cities were identified worldwide up to 2019
- These cities are primarily clustered in EU, Eastern Asia, and the northeastern US
- China has the highest number of shrinking cities, totaling 679

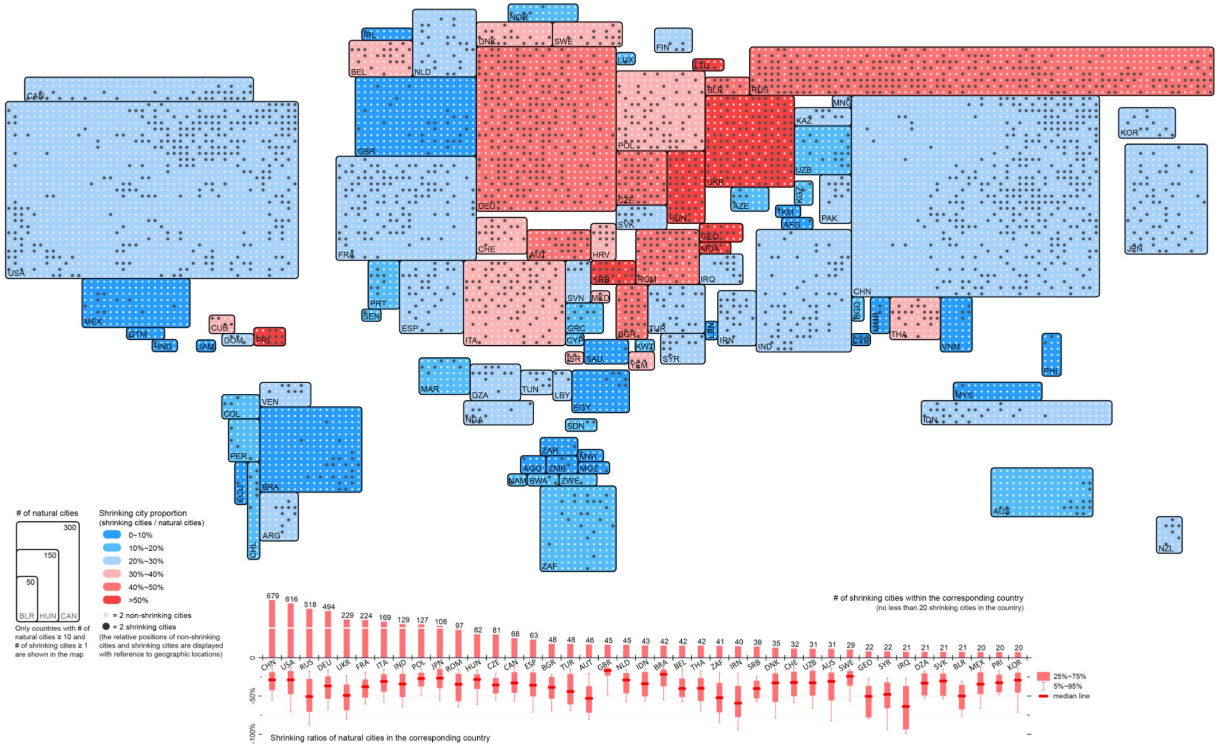

Fig.1 Flat cartogram of the spatial distribution of shrinking cities (SCs) on the globe and the SC proportion at the country level (Meng et al., 2021)

Brief Introduction to Pittsburg City

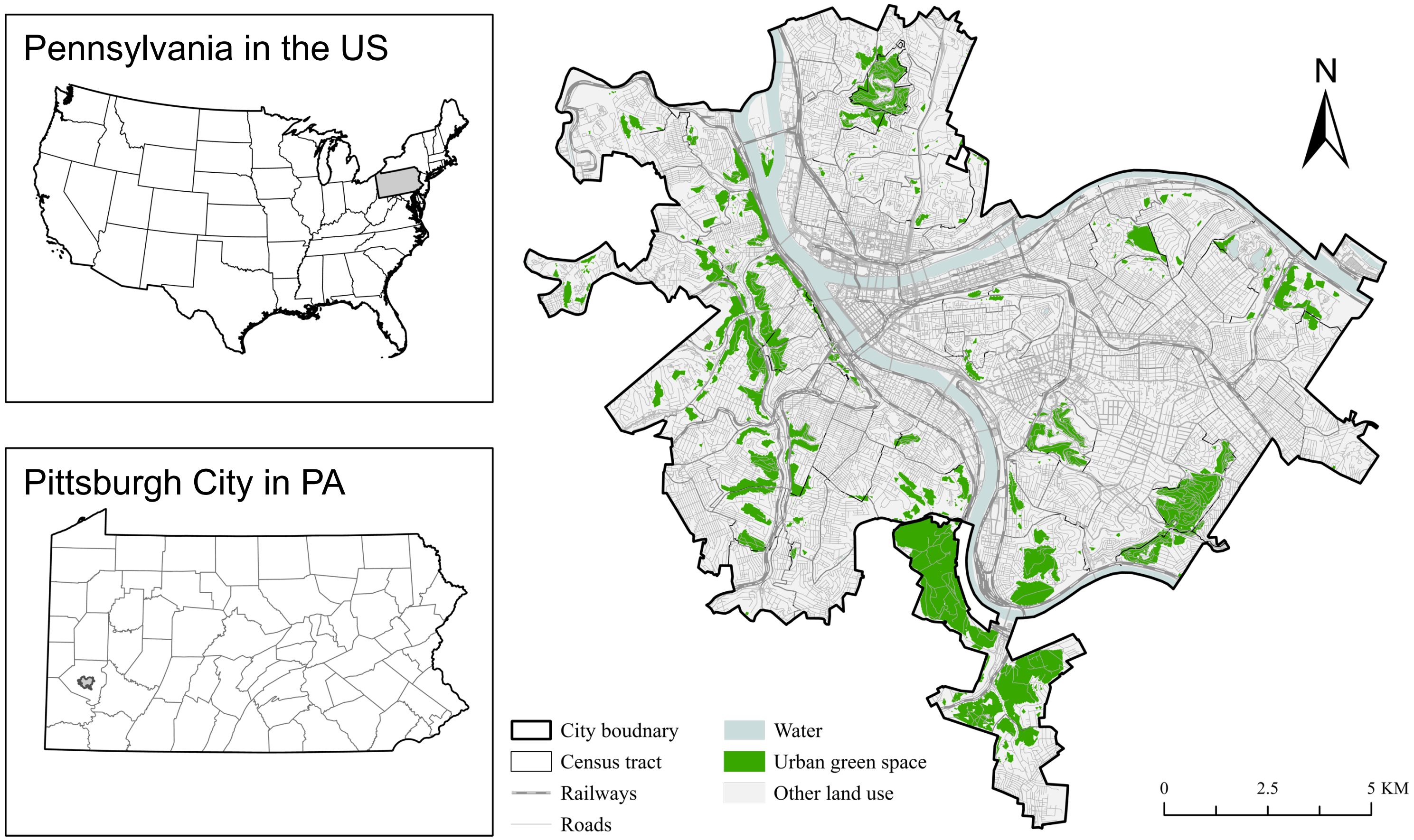

Fig.3 Location, urban context, and UGS distribution of Pittsburgh

- **Population Decline**: Continuous decrease from 1960 to 2022
- **Recent Decline Trends**: Average annual rate of **-0.42%** (2000-2022), about **-0.85%** (2010-2020)
- **Demographic Composition**: Predominantly White (64.5%), significant Black/African American (23.2%), with Asian (5.6%) and Hispanic/Latino (3.6%) minorities

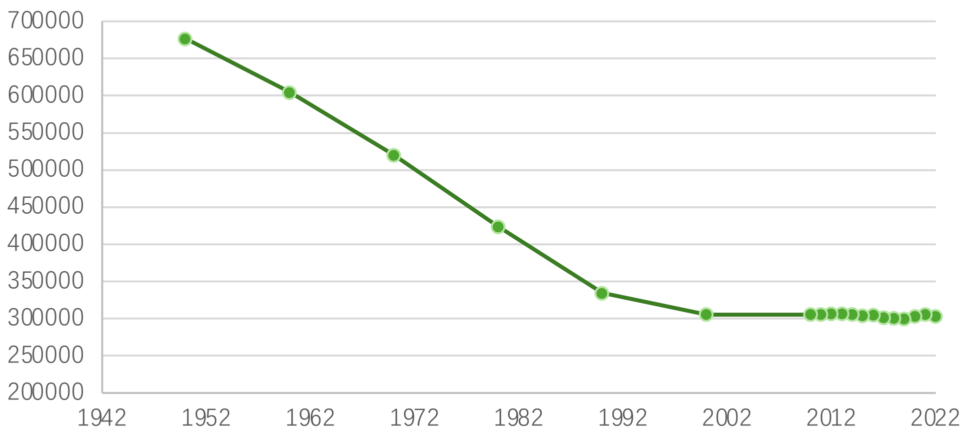

Fig.4 Population of Pittsburgh since 1950

Research Questions

1. **Factors affecting UGS changes in shrinking cities?**

2. **Role of UGS in community revitalization?**

What's Urban Green Space in Pittsburgh?

Challenges for UGS in shrinking cities

- Deteriorating urban infrastructure (Mullenbach et al., 2021)
- Inadequate maintenance of UGS (Sakamoto et al., 2018)
- Unequal distribution of UGS (Chen et al., 2023)
- Inefficient use of UGS (Park et al., 2020)

Kinds of parks in Pittsburgh City

- Regional Parks (1,920 acres in total)
- Community Parks (300 acres in total)
- Neighborhood Parks
- Riverfront Parks

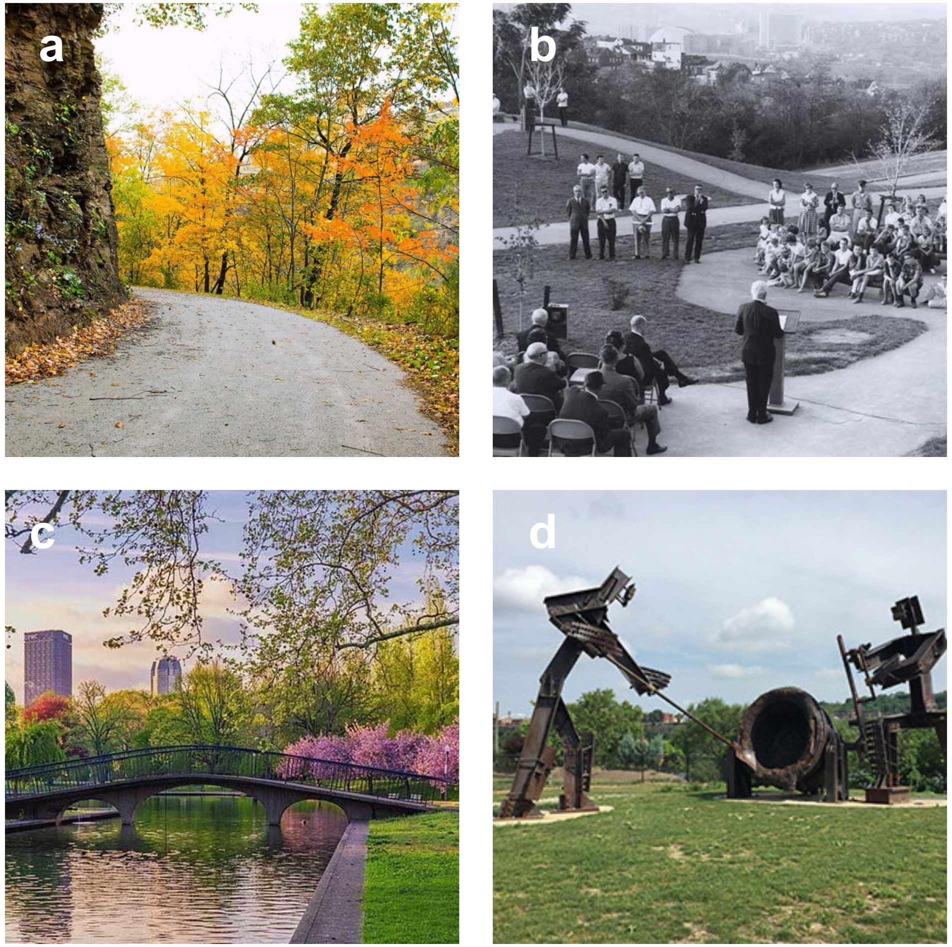

Fig.2 Different kinds of parks: (a) Frick Park, (b) South Side Park, (c) Allegheny Commons Park, and (d) South Shore Riverfront Park.

Research Gap

Current research progress and existing research gaps

Diverse perspectives

Understanding causes

Policy insights

Machine learning applications

Human-centric data utilization

Insufficient focus on community engagement

Post-pandemic adaptations

The impact of UGS on shrinking cities at census tract level

Research Workflow

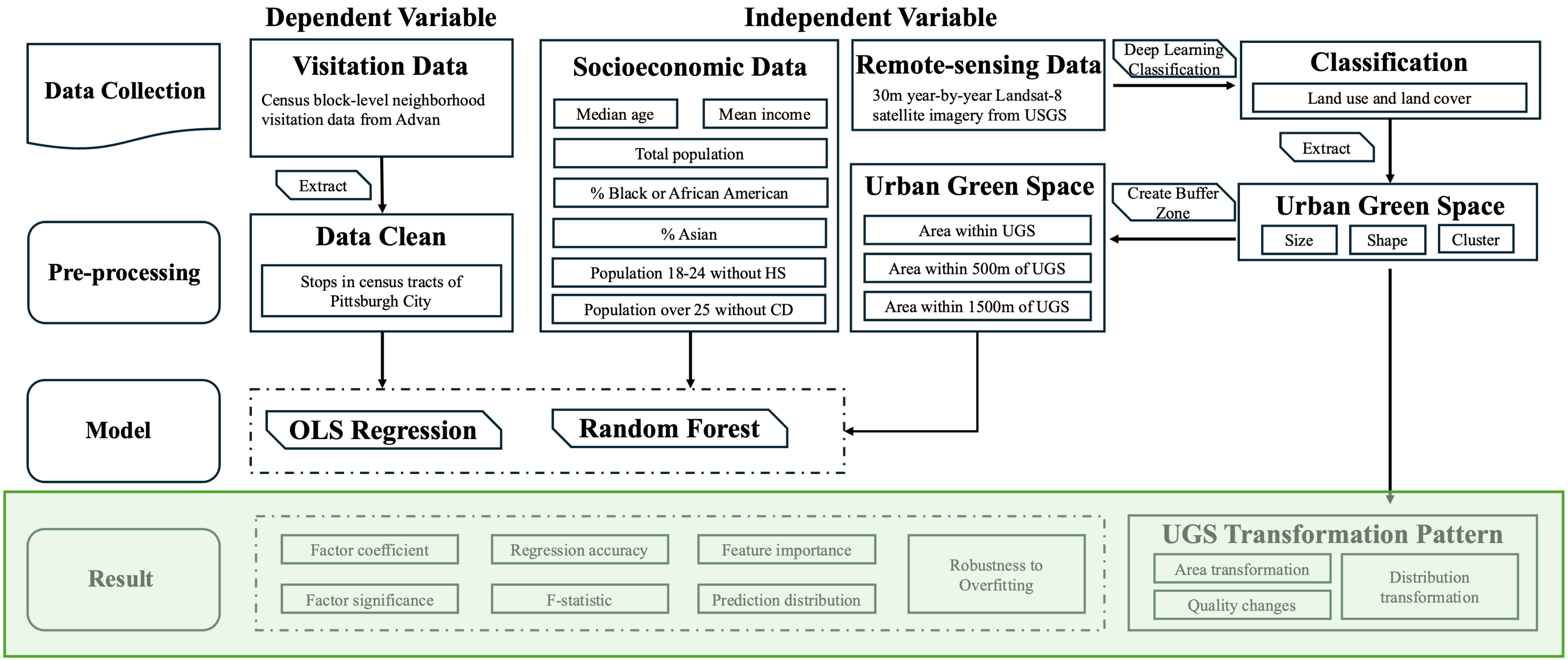

Fig.7 Research workflow for this study

Data source

Land Use data from USGS
(Landsat-8 at 30meters level)

American Community Survey (ACS)

Social and economic data from Census Bureau
(at census tract level)

Use POI's geometry

No filtering data

Differential privacy

Visitation data from ADVAN Neighborhood Pattern
(at census block group level every week)
This data is ideal for site-selection use and other use cases where you need to understand **how** busy an area is, **when** it is busy and the **demographics** of the visitors.

ML Analysis of Satellite Imagery

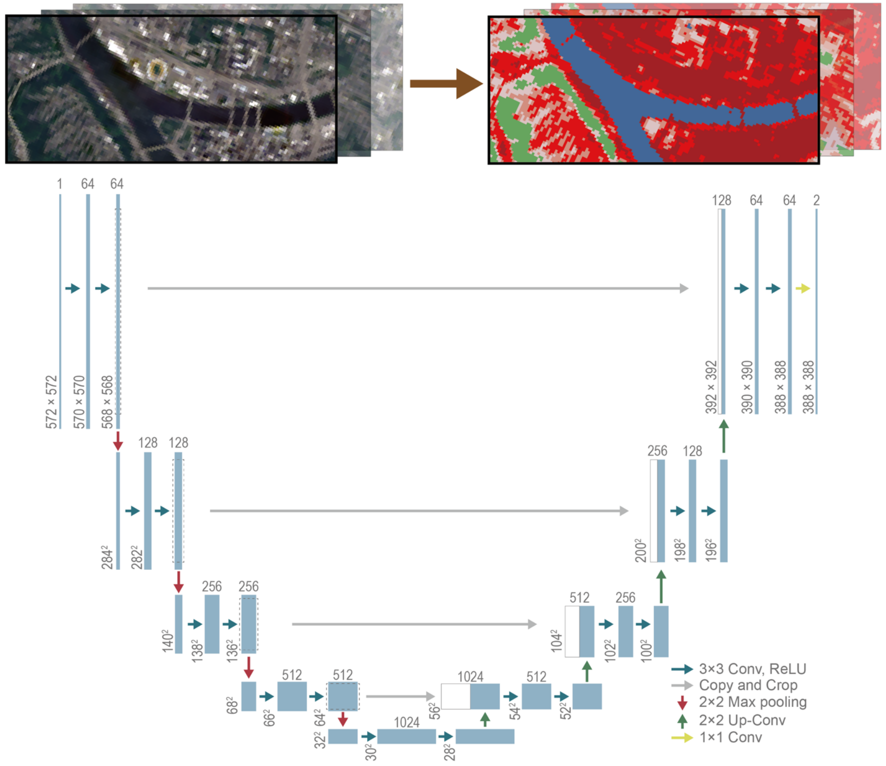

Fig.5 U-net model used in ML classification tasks

Why Using Landsat-8?

- Increased data acquisition
- Enhanced imaging capabilities
- Wide range of applications
- Quality control band

Why Using Land Cover Classification (Landsat 8) from Esri?

- Rich data sources
- Reliable classification results
- Low computational demand
- Easy to deploy

Census Tract Fine-grained Data

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Y

X: social-economic data

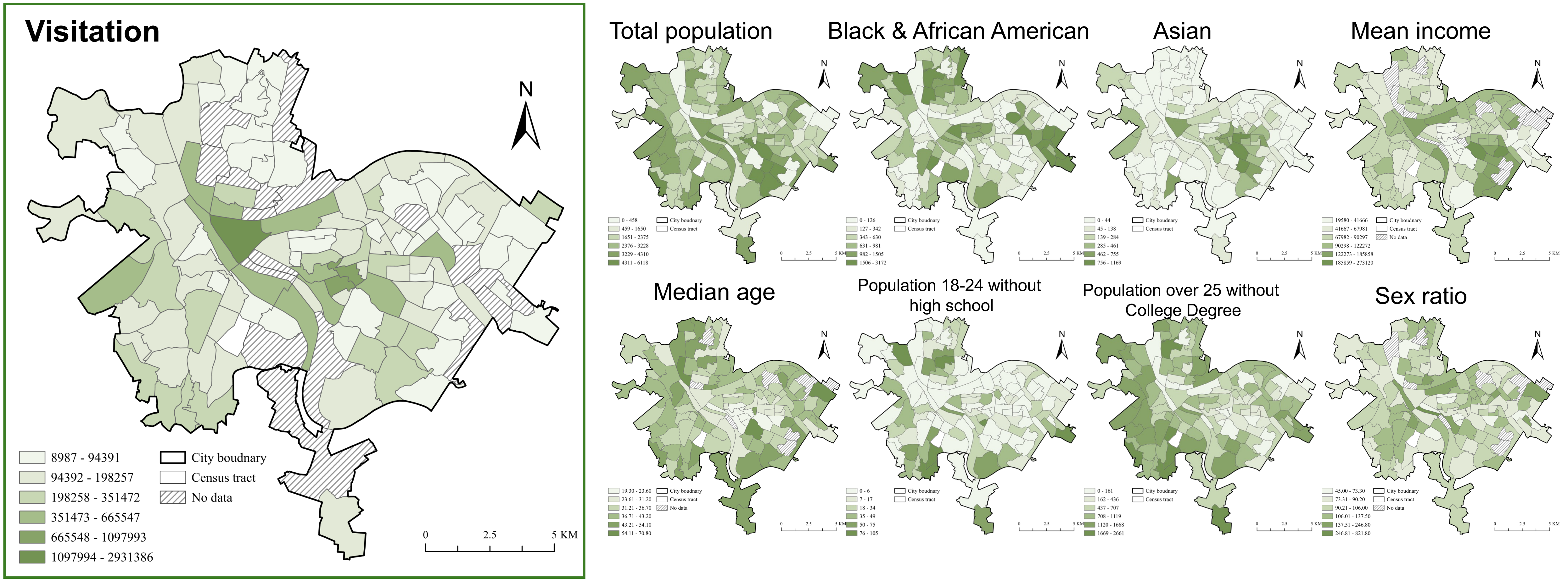
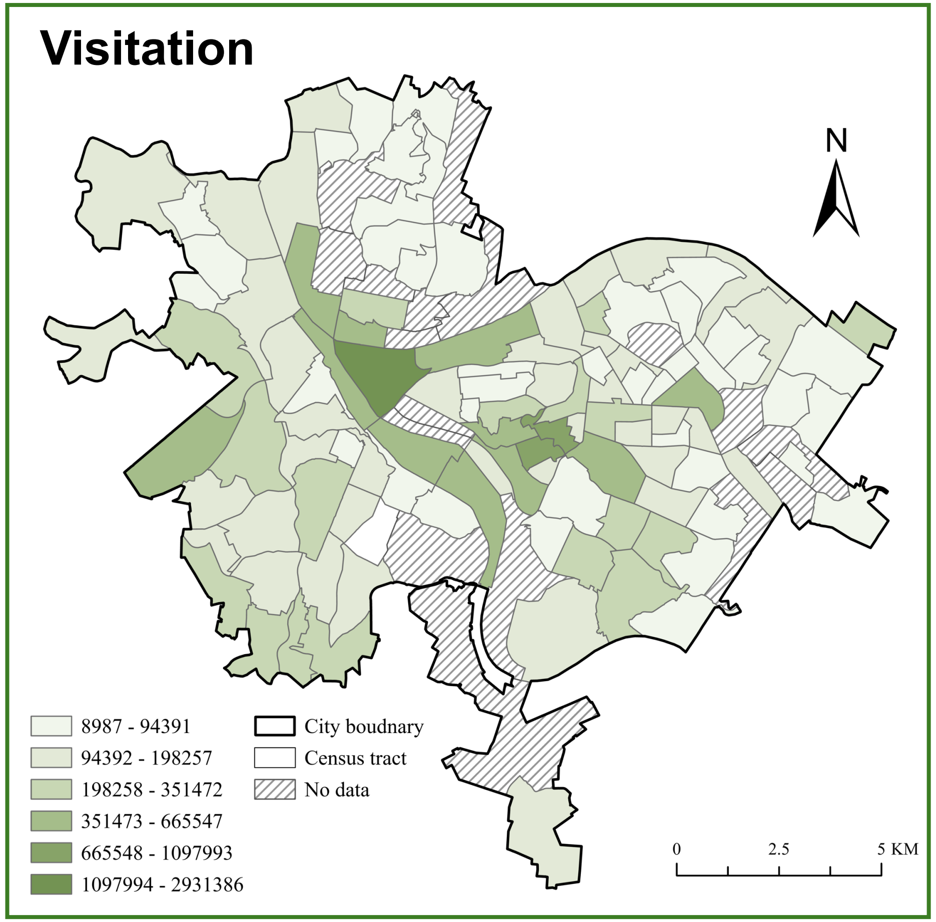


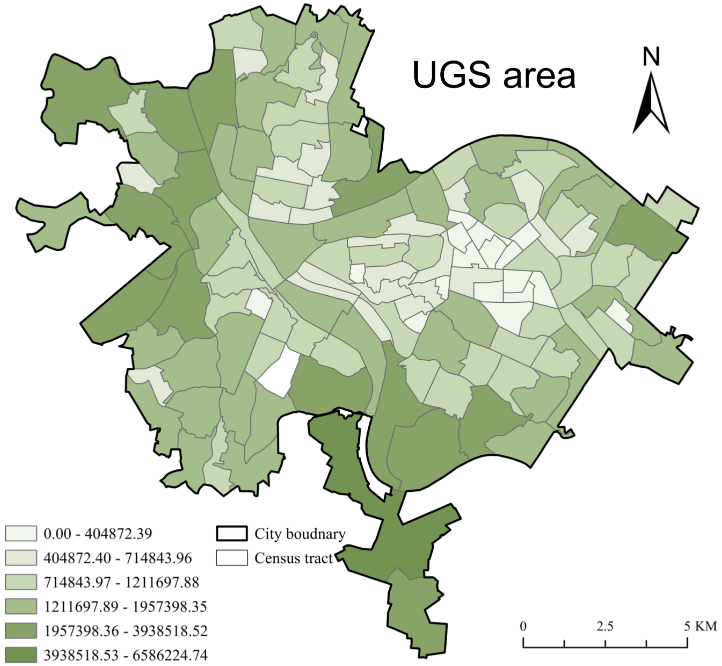
Fig.6-1 Spatial distribution of variables used in OLS regression

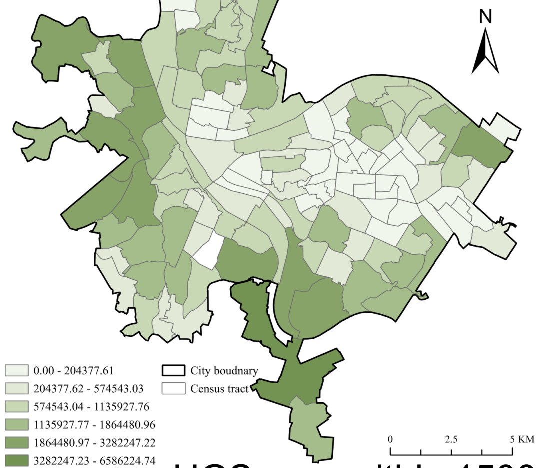
Census Tract Fine-grained Data

Y



X: UGS factors





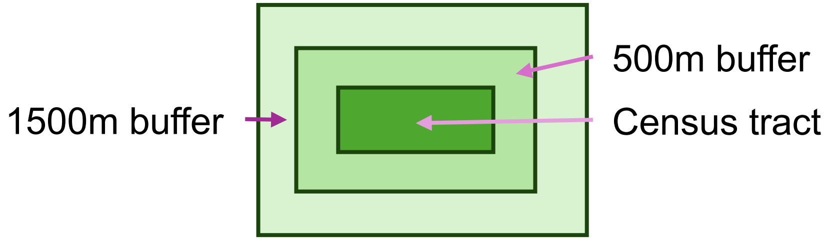


Fig.6-2 Spatial distribution of variables used in OLS regression

UGS Transformation Results

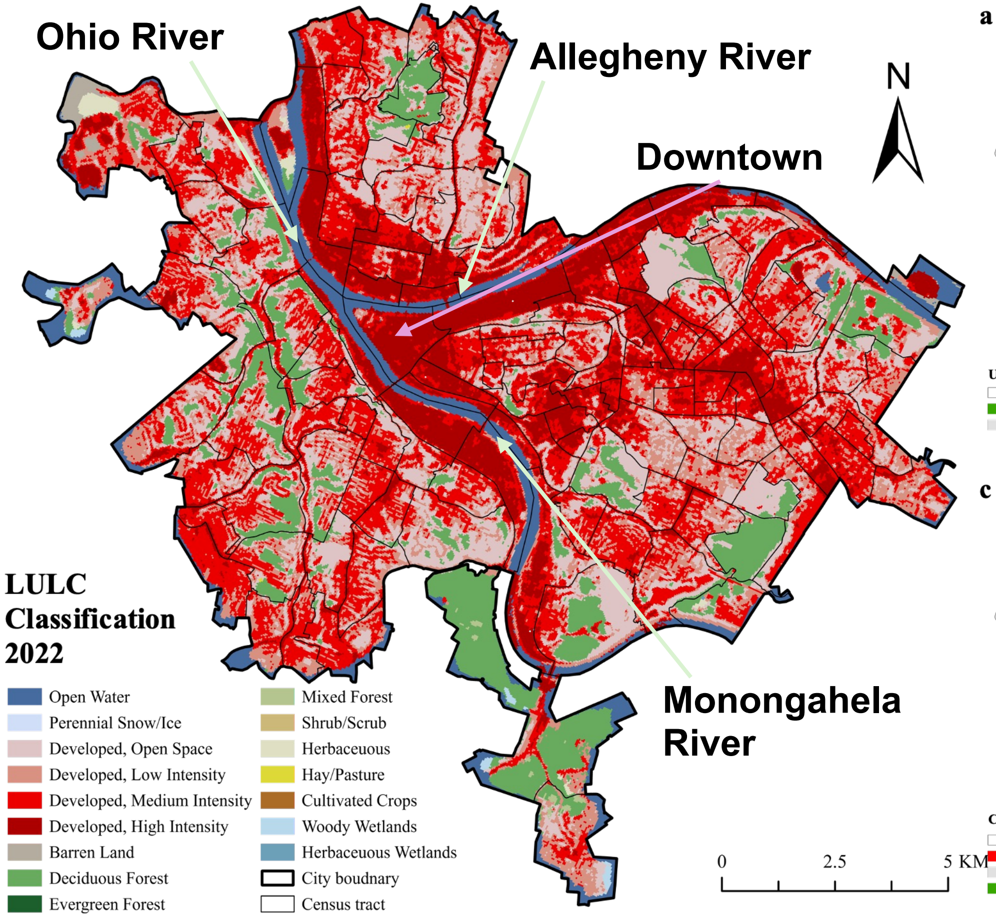


Fig.8 Land Use classification

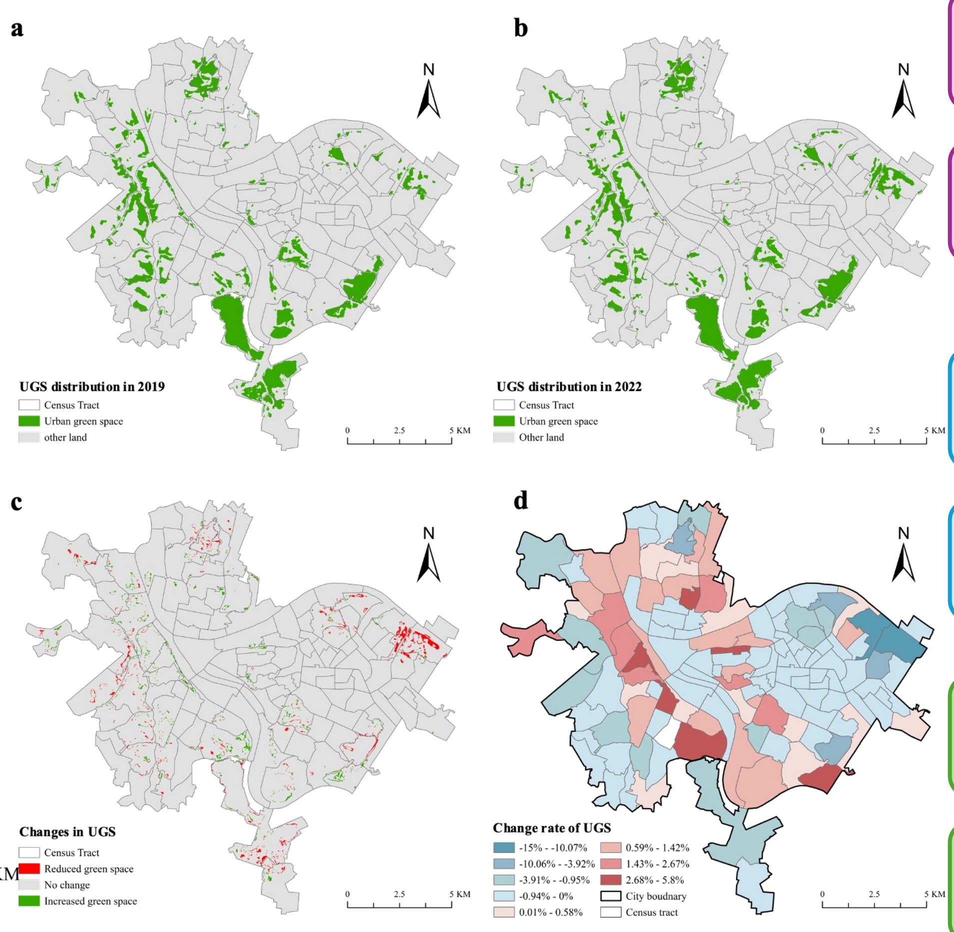


Fig.9 (a)Urban green space in 2022, (b)Urban green space in 2019, (c) change and (d) its change rate by census tract

2019: $16.20km^2$ (10.66%)

2022: $15.79km^2$ (10.38%)

Decrease in eastern hills

Scattered decreases in north and southwest

New greenway along Ohio River

Expansion around central area

OLS Regression Findings

Positive Correlations

- Total population
  - Except for 2021
- UGS area within 1500m
- Population over 25 without College Degree
  - Only in 2019

Not Significant

- Median age
- Mean income
- Sex ratio
- Racial
- Population between 18-24 without high schools

Negative Correlations

- UGS area within 500m
  - Especially in 2019 & 2022

Tab.1 Result of OLS Regression

	2019			2020			2021			2022		
	Coef	$P > \|t\|$	VIF	Coef	$P > \|t\|$	VIF	Coef	$P > \|t\|$	VIF	Coef	$P > \|t\|$	VIF
Total Population	297.042	0.001***	3.989	70.0953	0.024	4.511	48.609	0.120	4.441	98.151	0.087*	4.758
Median age	-4703.112	0.601	1.949	-1115.556	0.677	1.894	-2644.589	0.350	1.790	-3517.414	0.534	2.067
Mean income	-2.442	0.218	2.196	-0.842	0.227	2.544	-0.327	0.629	2.601	-1.715	0.155	3.014
Sex ratio	-2550.199	0.380	1.208	-316.110	0.725	1.181	151.403	0.855	1.126	277.296	0.841	1.113
Black and African American	13.647	0.903	1.686	-15.717	0.674	1.534	-16.790	0.621	1.484	-53.871	0.373	1.612
Asian	-380.443	0.149	2.368	-19.202	0.833	2.449	67.737	0.481	2.320	19.036	0.916	2.440
Popu 18-24 without HS	-1237.094	0.586	1.635	-669.129	0.303	1.264	-495.394	0.403	1.142	-1303.365	0.265	1.286
Popu over 25 without CD	-473.632	0.018	4.118	-108.176	0.108	4.519	-70.351	0.265	4.040	-180.690	0.153	4.942
Sum_area_500	-0.497	0.008*	7.292	-0.152	0.010*	6.756	-0.105	0.075	6.092	-0.377	0.001***	7.547
Sum_area_1500	0.495	0.001***	4.757	0.189	0.000***	4.871	0.138	0.002**	3.976	0.419	0.000***	5.966
Sum_area	0.418	0.435	3.310	0.044	0.799	3.080	0.058	0.746	3.216	0.241	0.398	2.758

$r^2_{2019} = 0.342$ $r^2_{2020} = 0.554$ $r^2_{2021} = 0.305$ $r^2_{2022} = 0.334$

WHY?

In the stereotype, the larger the UGS surrounding a census tract, the more it is expected to be visited, as there are green areas nearby.

GWR Analysis: Green Inside Census Tract

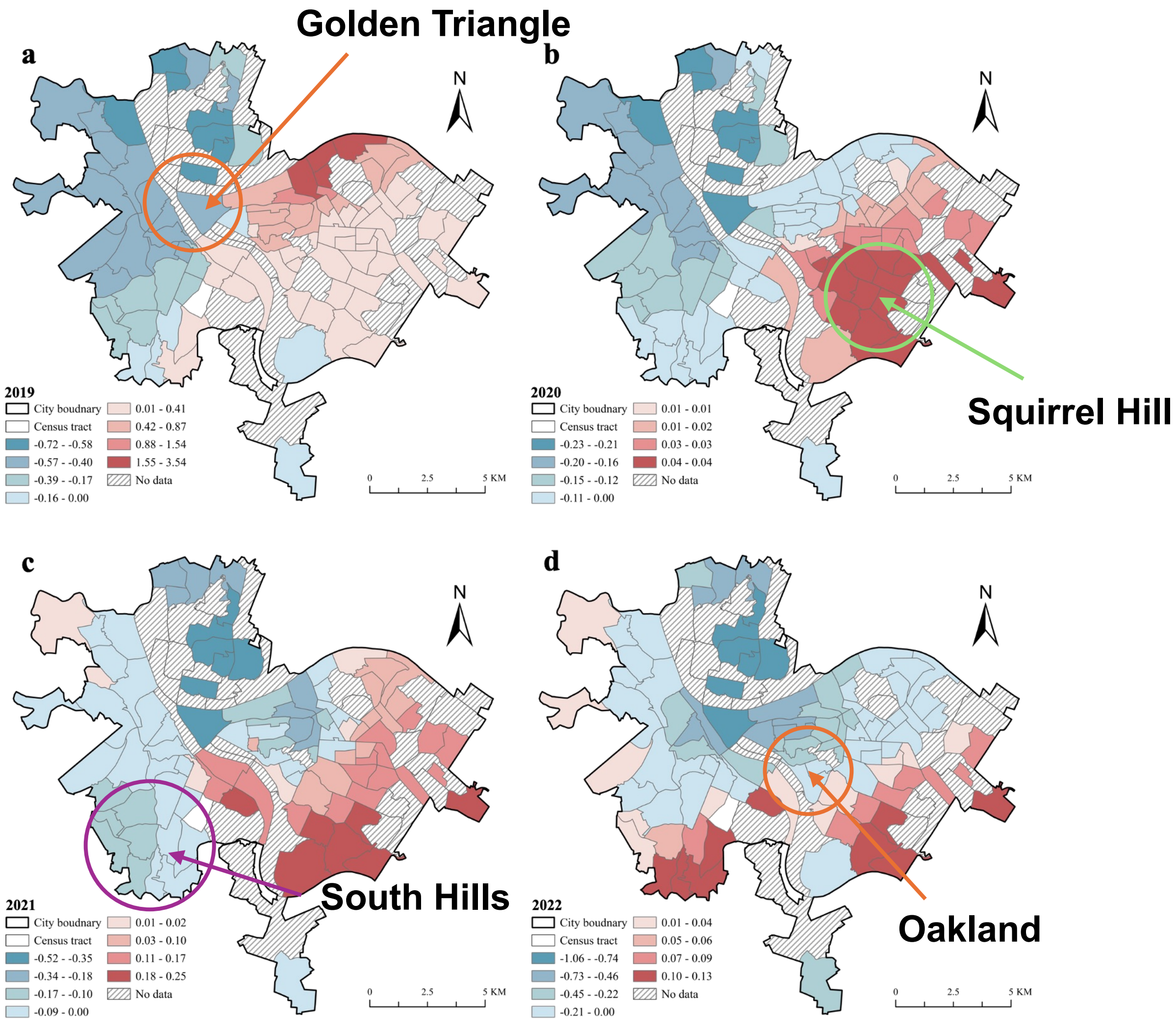


Fig.10 Regression coefficients for visitation and UGS area within census tract of the GWR model for each year.

Reginal Variation

- Central & Northern Districts
  - Negative influence of UGS area on visitation, most pronounced downtown (the Golden Triangle)
- East Districts
  - Positive influence, intensifying near urban periphery (e.g., Squirrel Hill South)

Yearly Trends

- Urban Population Decline
  - Expands negative UGS-visitation correlation.
- East District Shift
  - Positive (2019) to negative (2022) in Oakland, impacting major institutions.
- Southern Hills (Brookline, Carrick, Overbrook)
  - Cyclical trend; positive in 2019, negative 2020-21, returning to positive in 2022.

GWR Analysis: Green around Census Tract

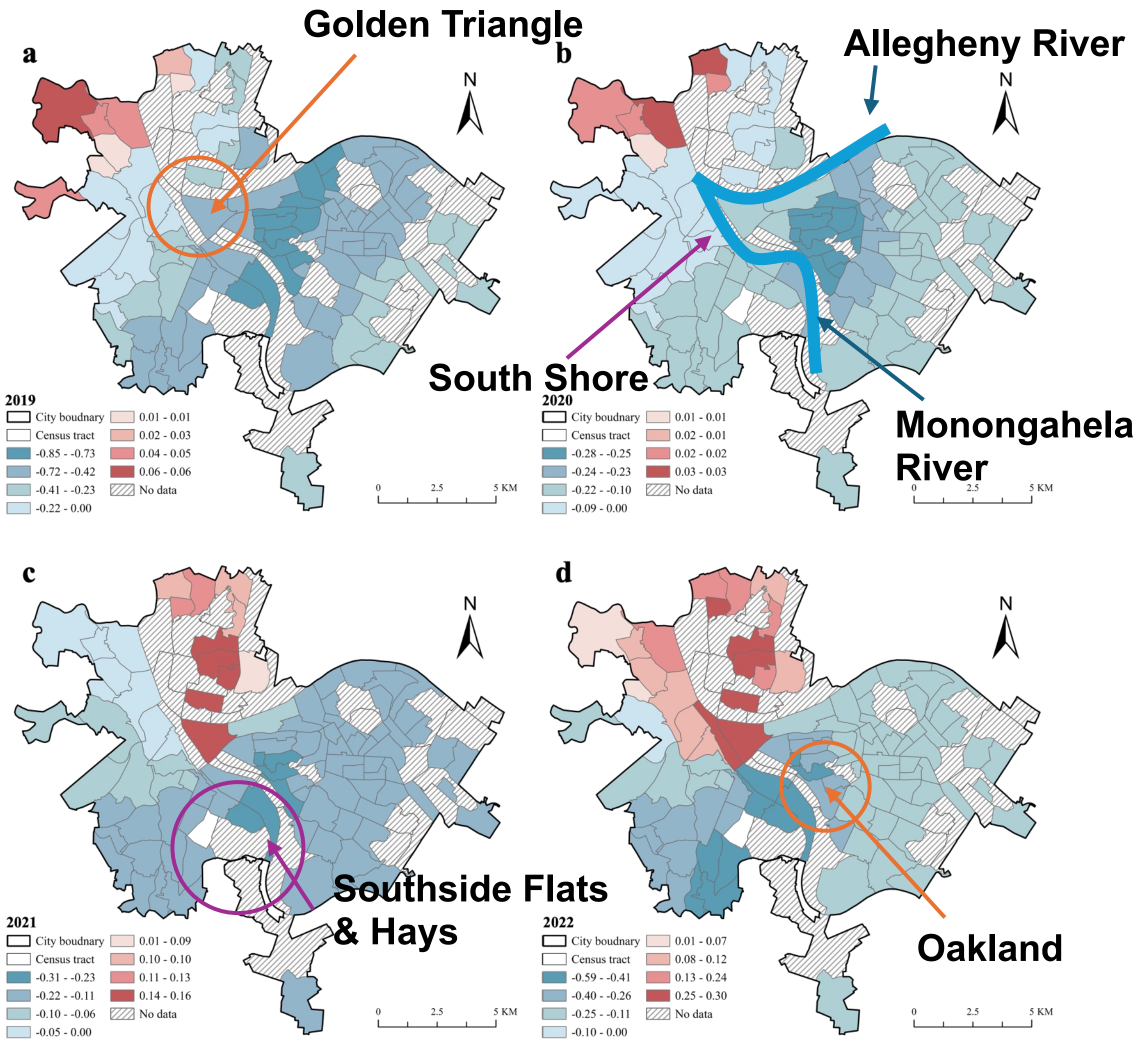


Fig.11 Regression coefficients for visitation and UGS area with a 500m radius of census tract of the GWR

Spatial Trends

- Negative Correlation
  - Expands negative UGS-visitation correlation
- Shift Over Time
  - Transition from negative to positive correlation in **downtown** and north of the Allegheny (low-density areas like Manchester and Troy Hill).
  - **South Shore**: Renewal efforts see shift from negative to positive correlation (RiverParc by Pittsburgh Cultural Trust).

Consistent Patterns

- Oakland (education/healthcare hub)
  - Maintains strong negative correlation, unaffected by population trends.
- Southside Flats & Hays
  - Similar stable negative correlation, especially in non-residential zones (entertainment/agricultural areas).

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Why UGS in 500m radius lead to decrease in visitation?

Competition for commercial land?

Functional redundancy?

Population dispersion effect?

Safety concerns?

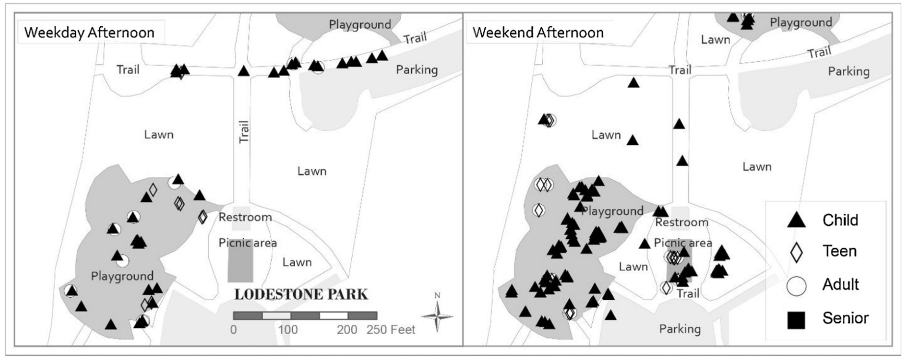

Fig.12 A comparison of behavior maps between different days of a week (Park et al., 2020)

BUT GWR shows UGS within 500m in CBD has **positive** influence on vitality

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What's the impact of COVID-19?

Pre-pandemic

- Strong **positive** correlation between total population and visitation rates
- Higher population density corresponded with increased community activity

During pandemic

The relationship between population and visitation rates became statistically **insignificant**

- Social distancing measures
- Remote work adoption
- Closure of public spaces
- Restricted social interactions
- Decreased intra-community population mobility

Post-pandemic

Return of positive correlation between population and visitation rates

- Widespread vaccine availability
- Relaxation of preventive measures
- Gradual resumption of community activities

Recap of this research

Influence of UGS Distribution on Community Vitality

- Within census tract
- **500m radius**

Impact of COVID-19

- Positive correlation between population and visitation
- This link became non-significant during the pandemic

Land Use Types and Visitation

- Commercial Districts
- Education and Healthcare Hubs
- Residential Areas

UGS planning amid Urban Shrinkage

- UGS planning can counteract urban shrinkage by enhancing community vitality

Key References

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