Exposure Beyond Mass:
High-Spatial Resolution Exposure to Source-Resolved Atmospheric Particle Number and Chemical Mixing State
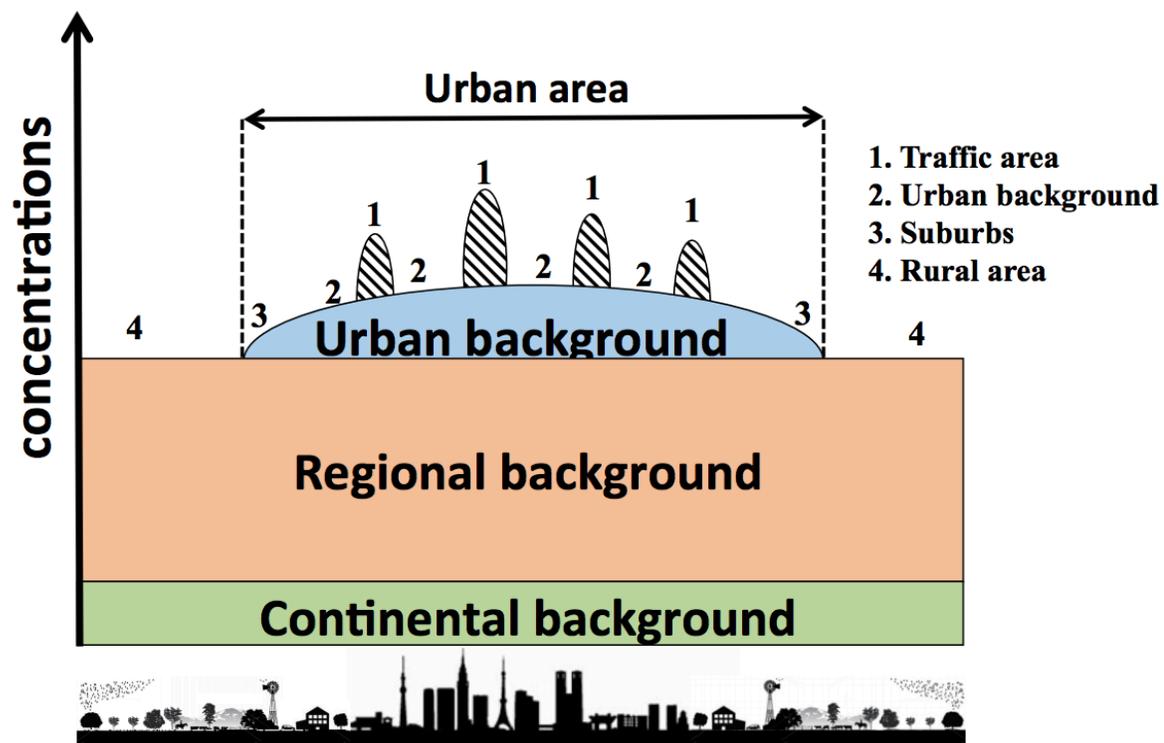
Qing Ye, Hugh Z. Li, Peishi Gu, Ellis S. Robinson, Joshua S. Apte, Ryan C. Sullivan, Allen L. Robinson, Neil M. Donahue, and Albert A. Presto
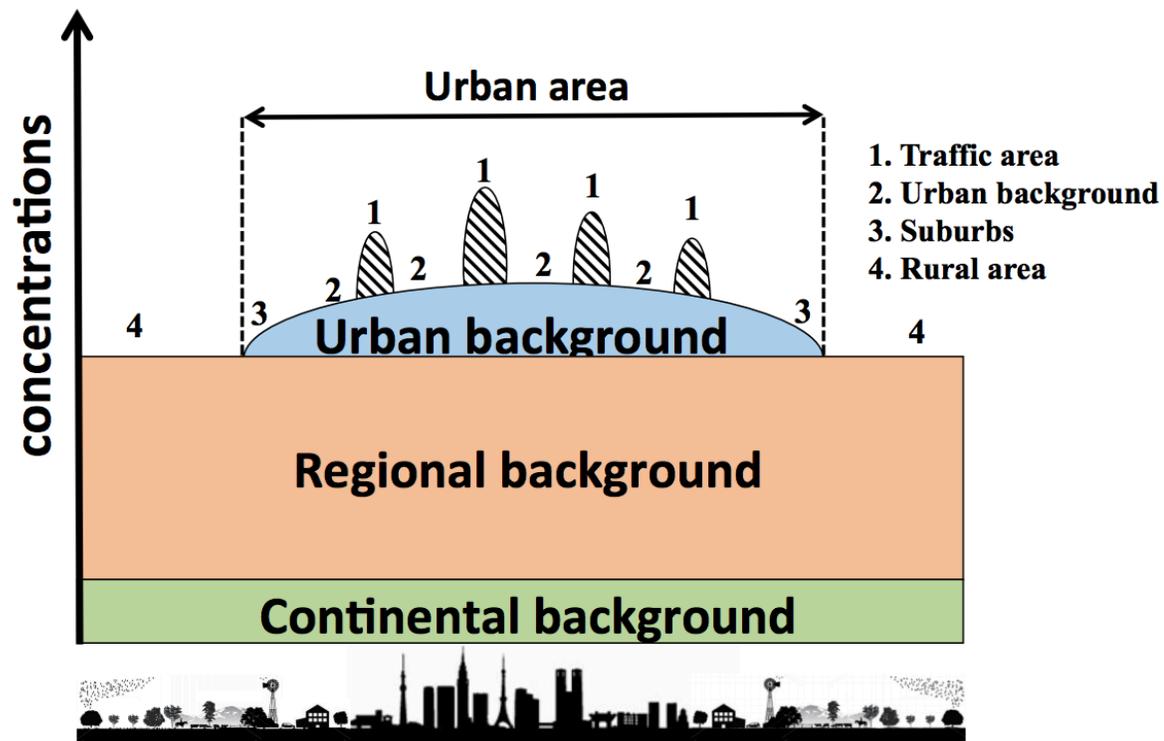
CACES

CAPS
Center for Atmospheric Particle Studies

Carnegie Mellon University

Concentrations of air pollutants in urban areas have strong spatial heterogeneities

1. Traffic area
2. Urban background
3. Suburbs
4. Rural area
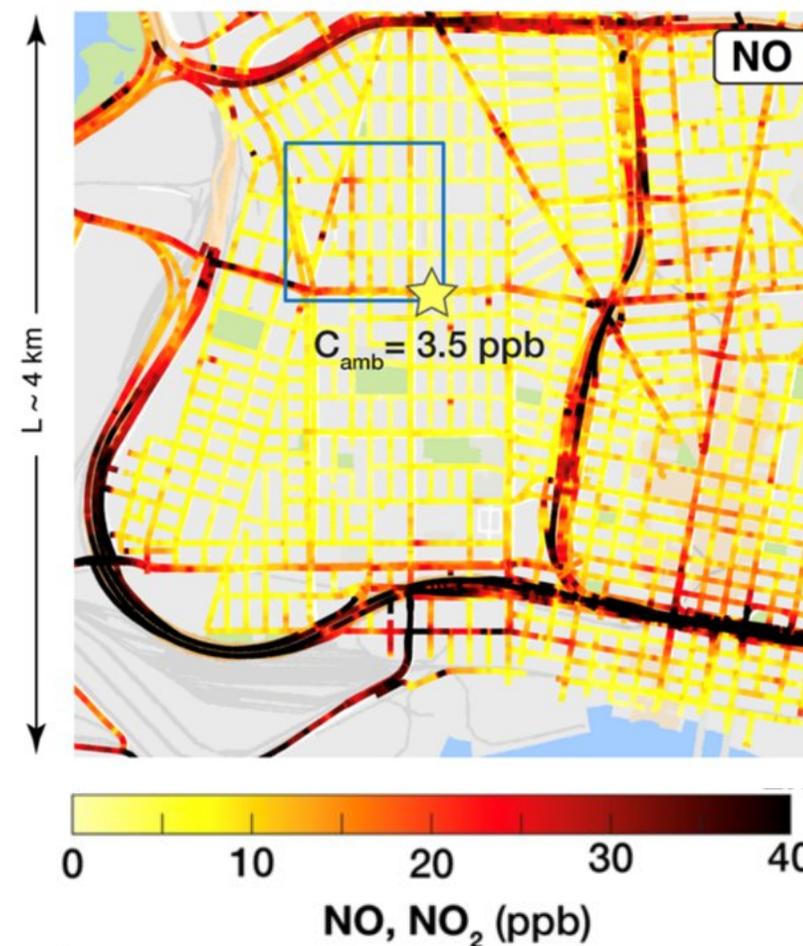
Fuzzi *et al*., 2015

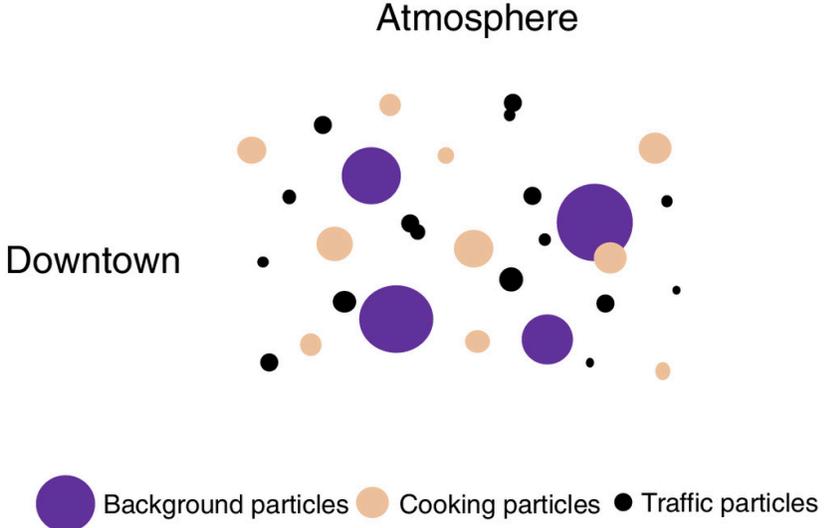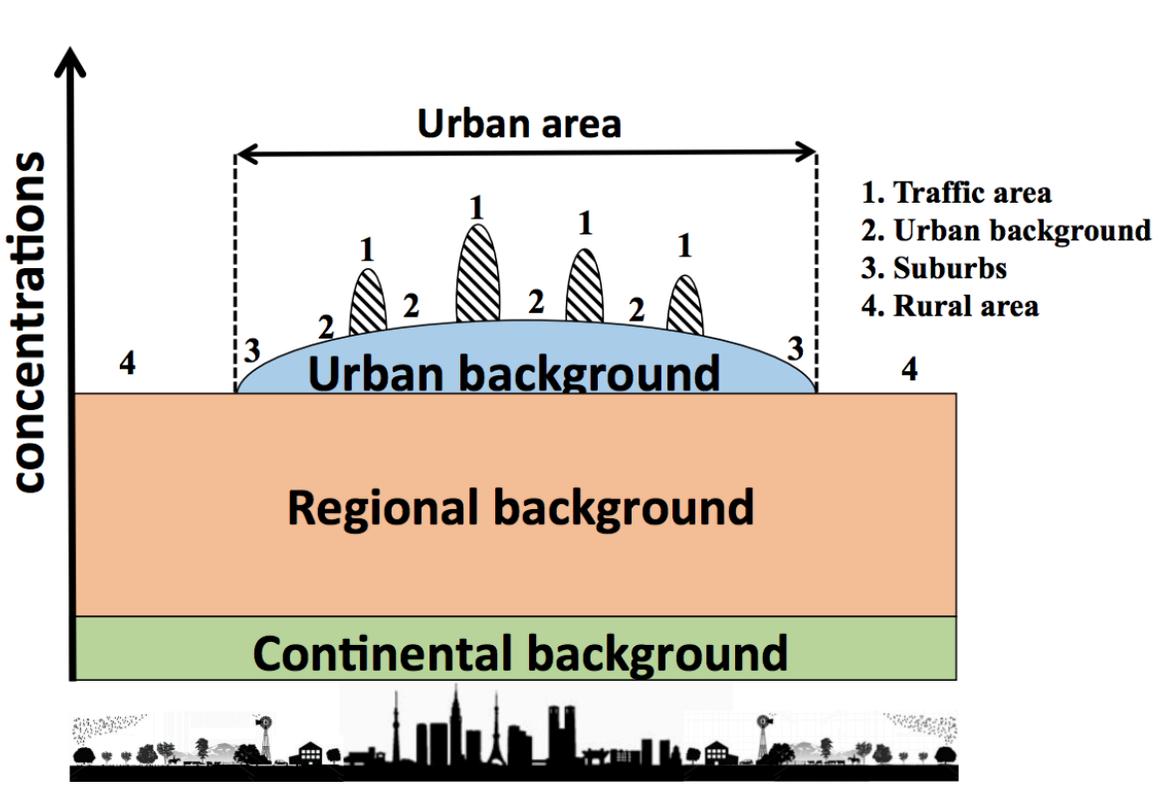# Concentrations of air pollutants in urban areas have strong spatial heterogeneities
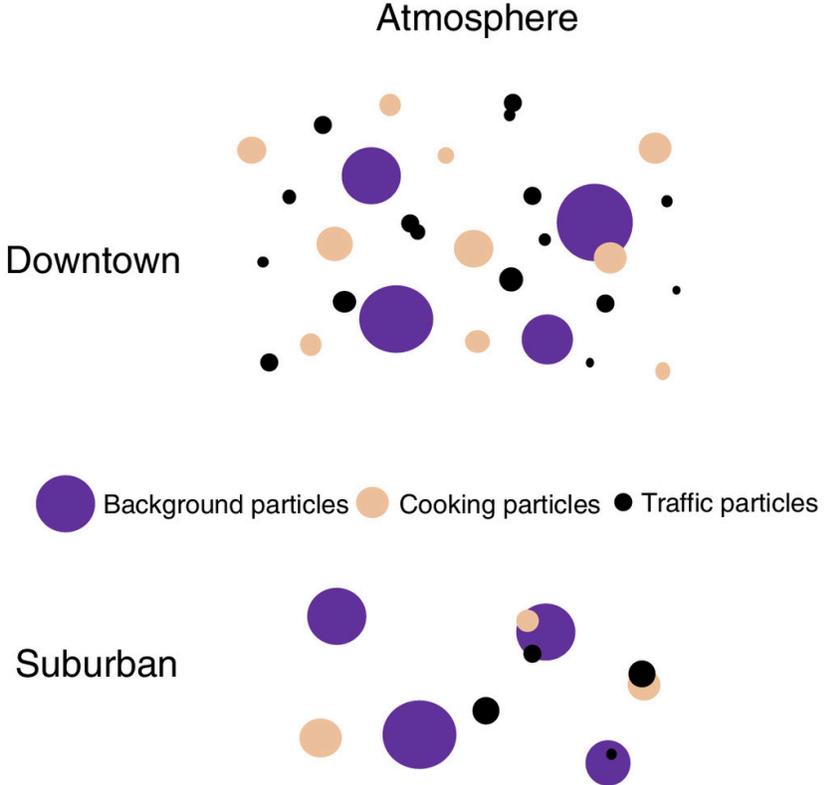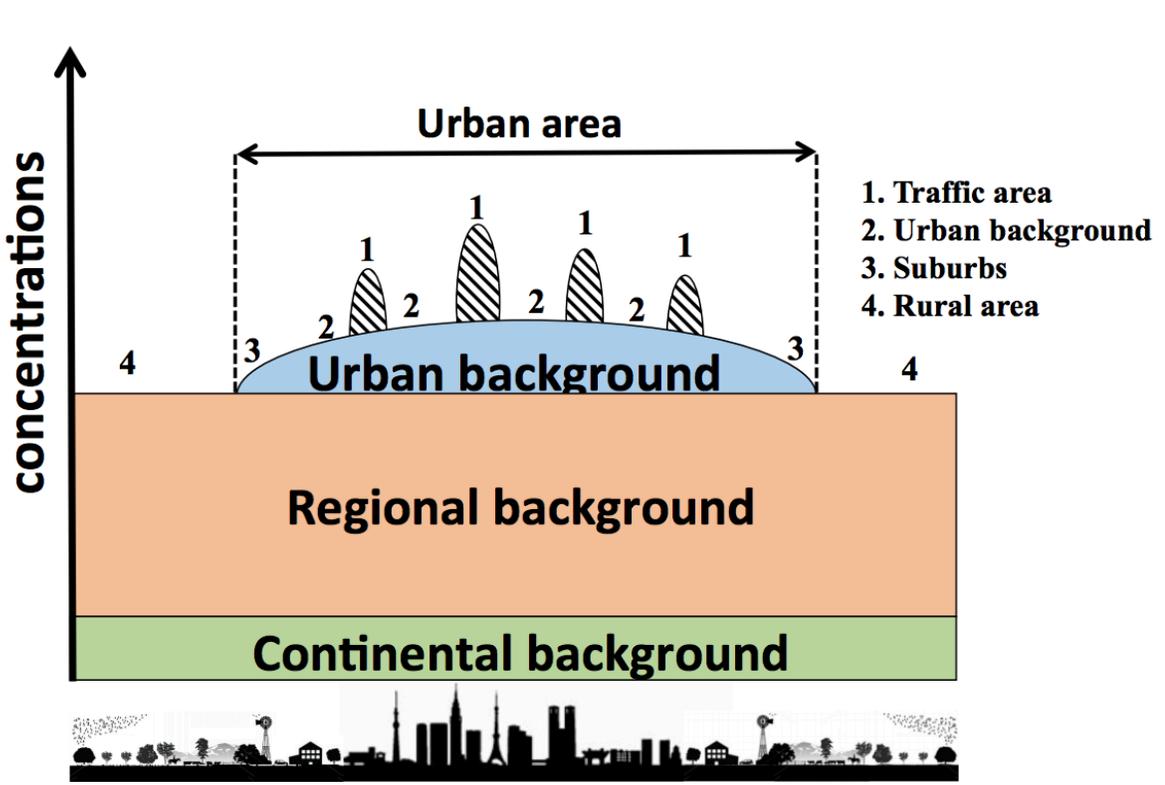

Fuzzi et al., 2015

Apte et al., 2017

1

Particulate matter pollution has more complexities in physiochemical properties
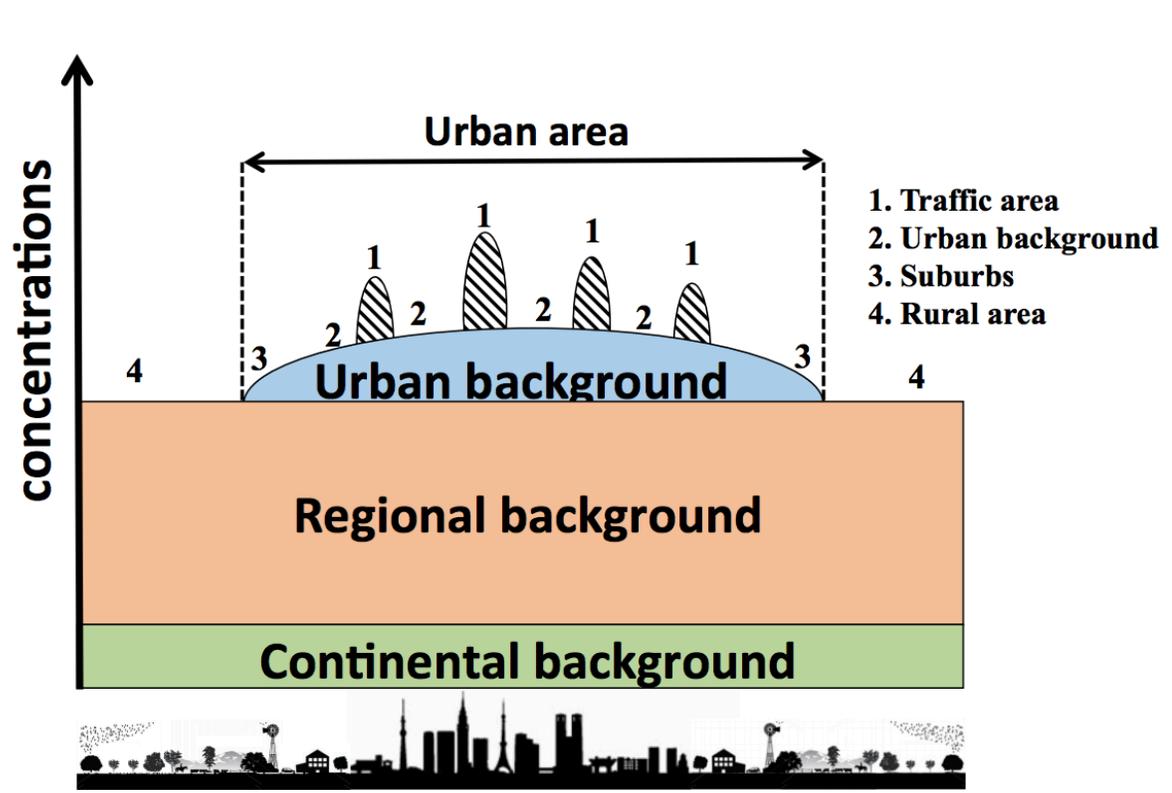

Fuzzi *et al*., 2015

Particulate matter pollution has more complexities in physiochemical properties
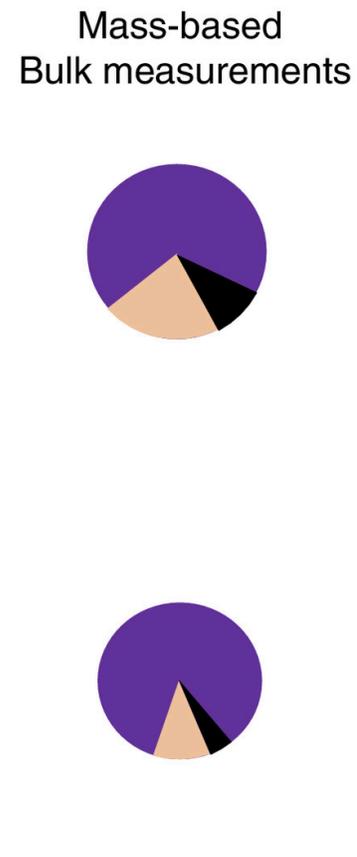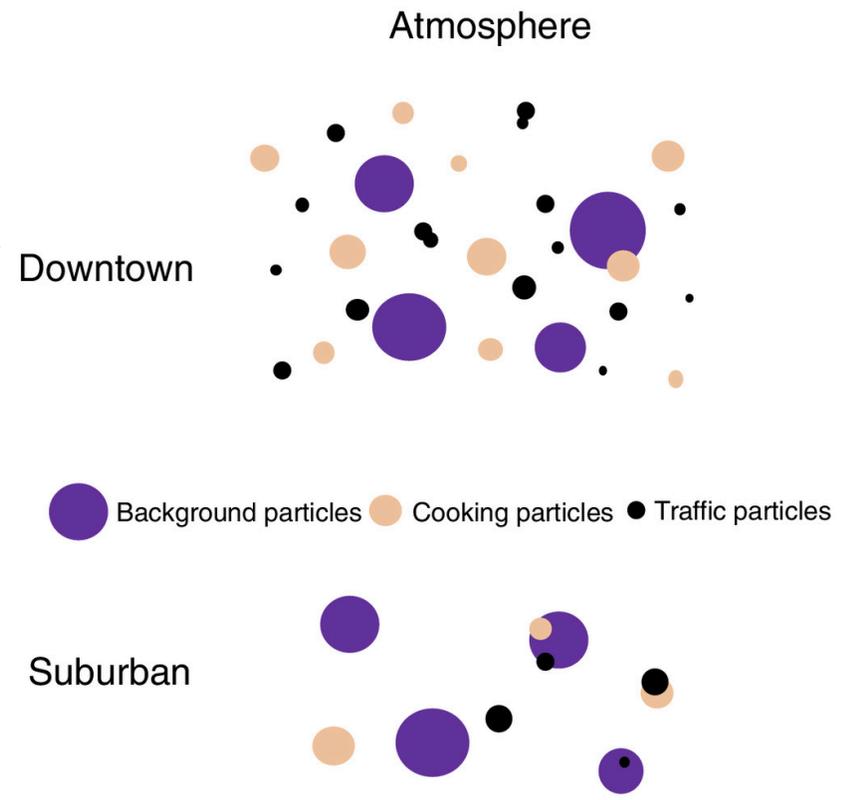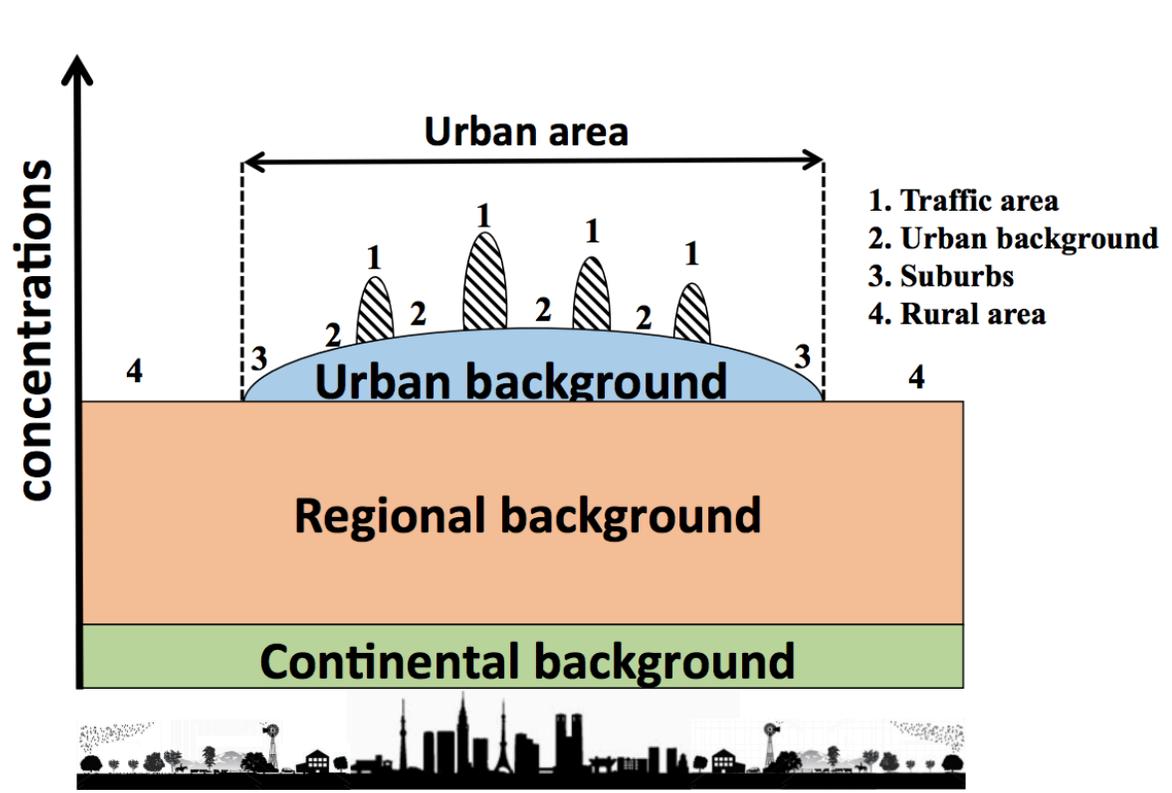

Fuzzi *et al*., 2015

Bulk mass-based filter measurements may not be sufficient to capture complexities
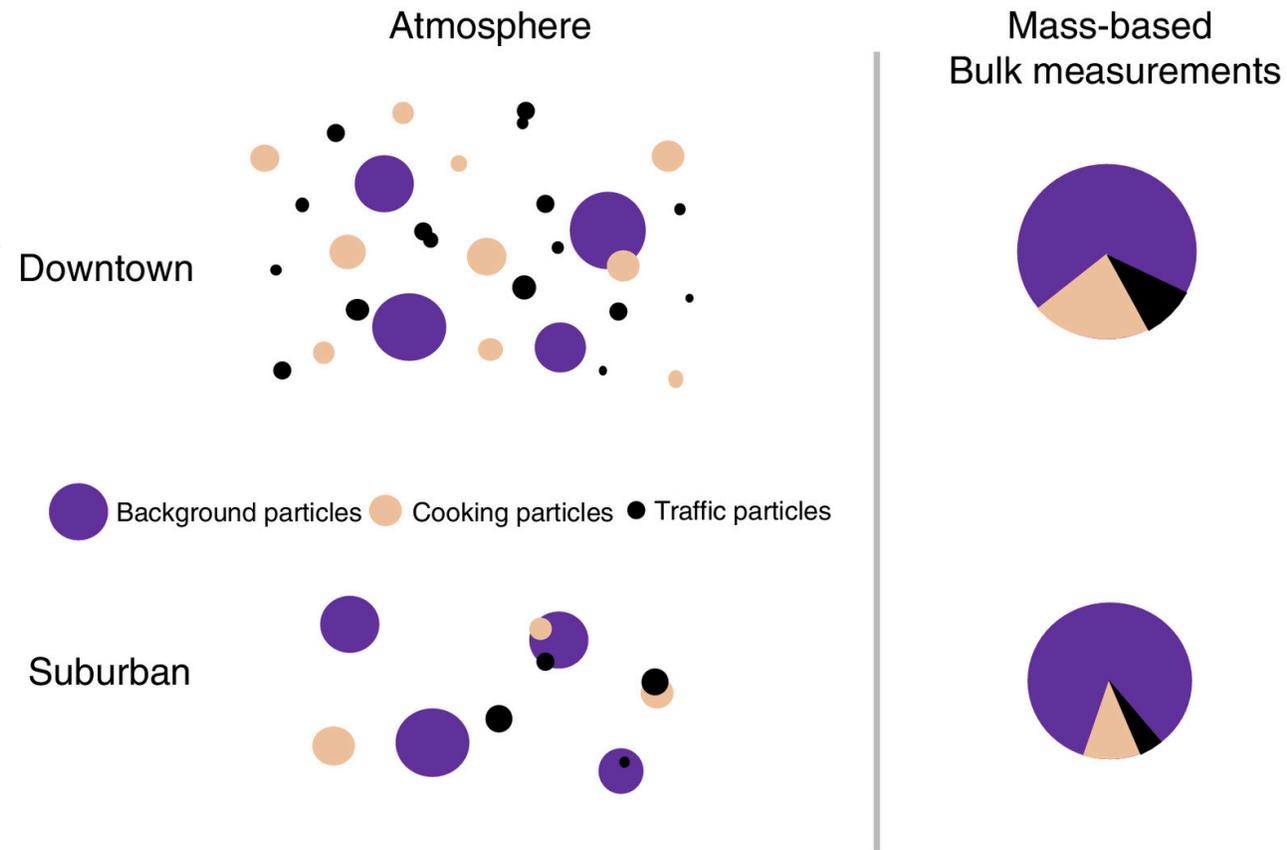

Fuzzi *et al*., 2015

Bulk mass-based filter measurements may not be sufficient to capture complexities
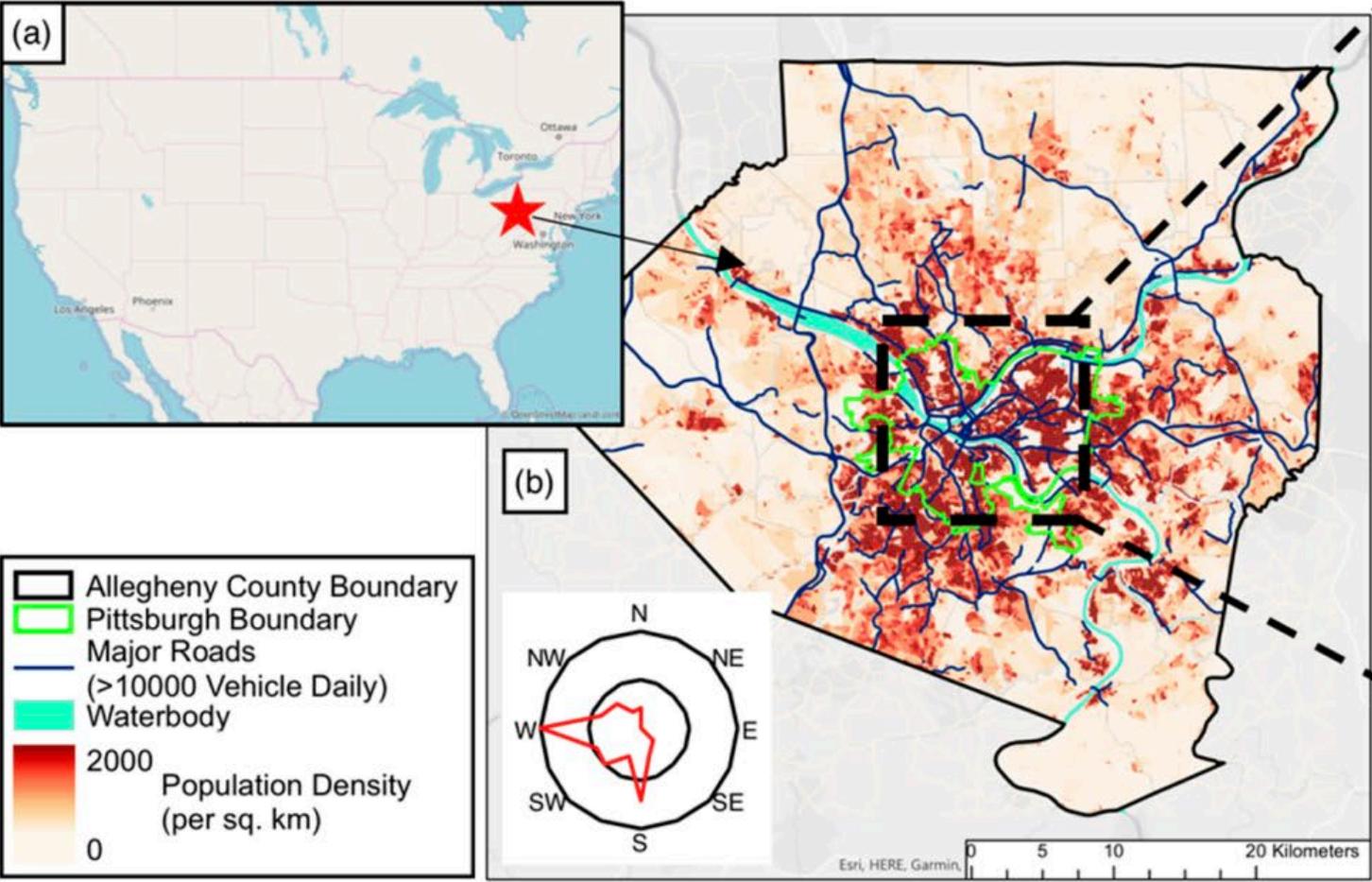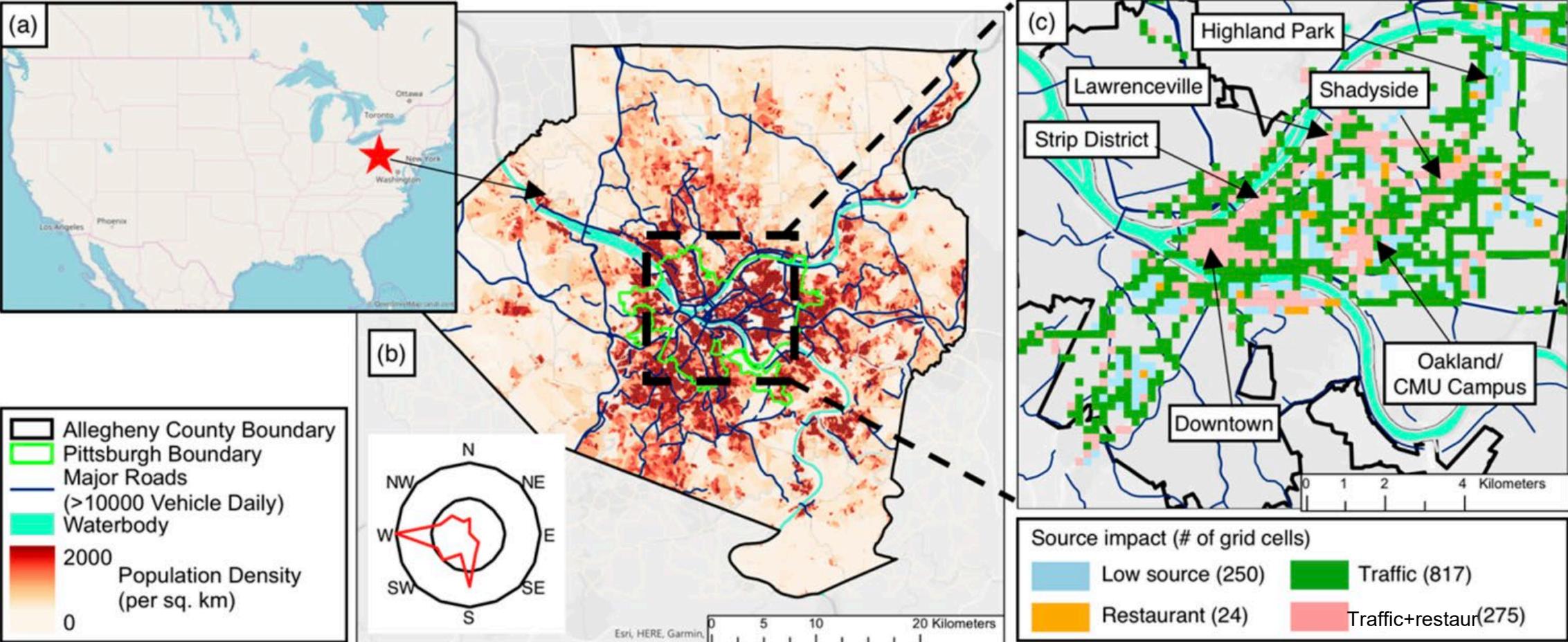

Fuzzi *et al*., 2015

What are the spatial patterns of PM exposure in different particle metrics?

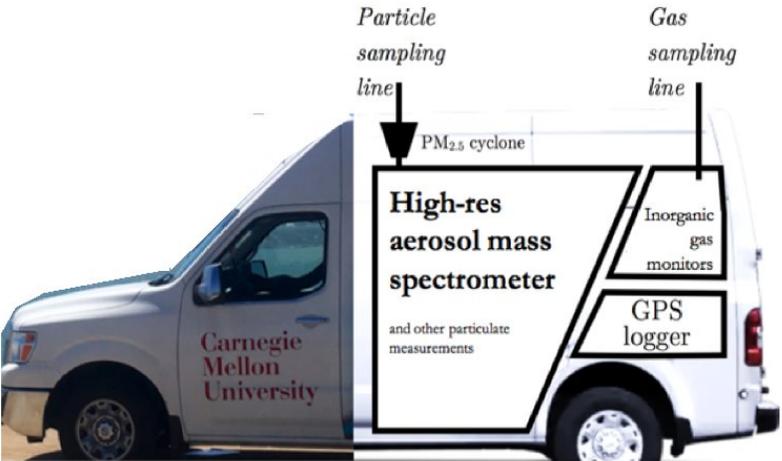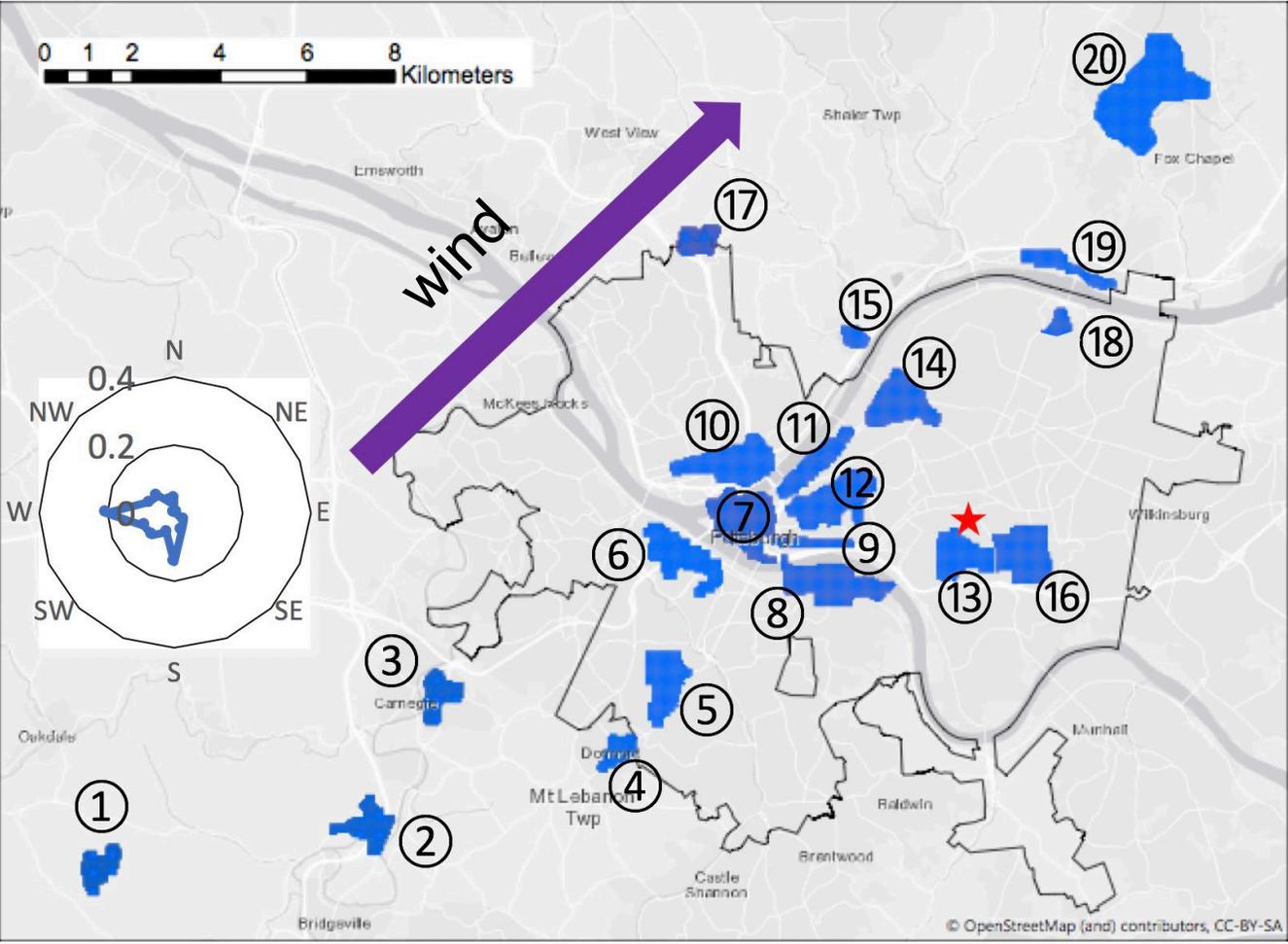# Overview of the sampling location---Pittsburgh PA

Gu *et al.*, 2019

Overview of the sampling location---Pittsburgh PA
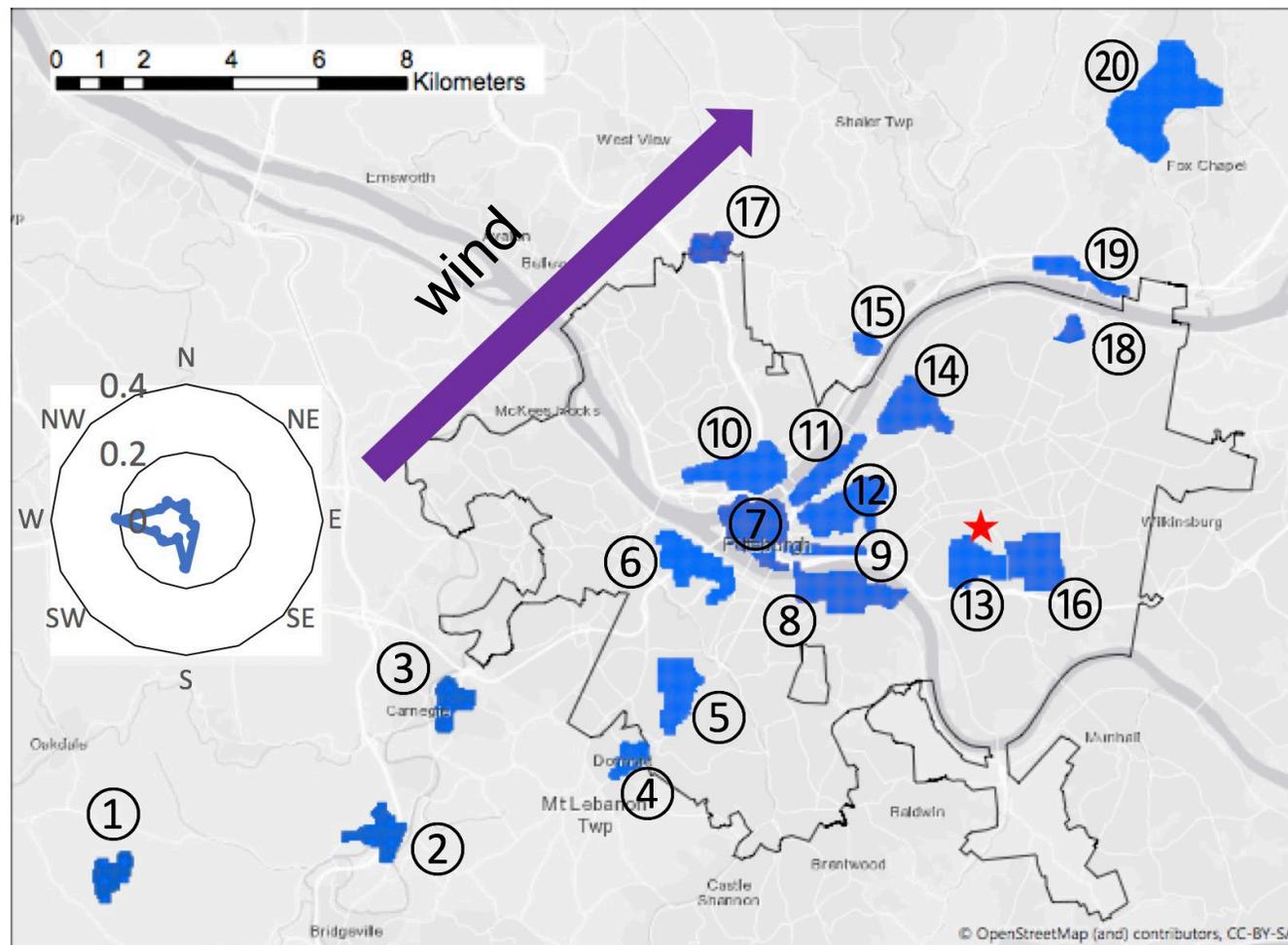
Spatially variable emission sources

Gu *et al*., 2019

Conduct repeated mobile sampling in Pittsburgh to map PM pollution

Single-particle mass spectrometry resolves individual particle's composition and source
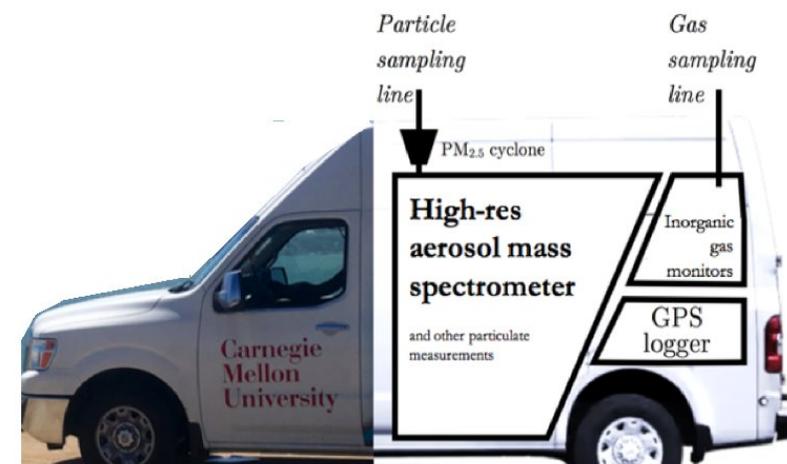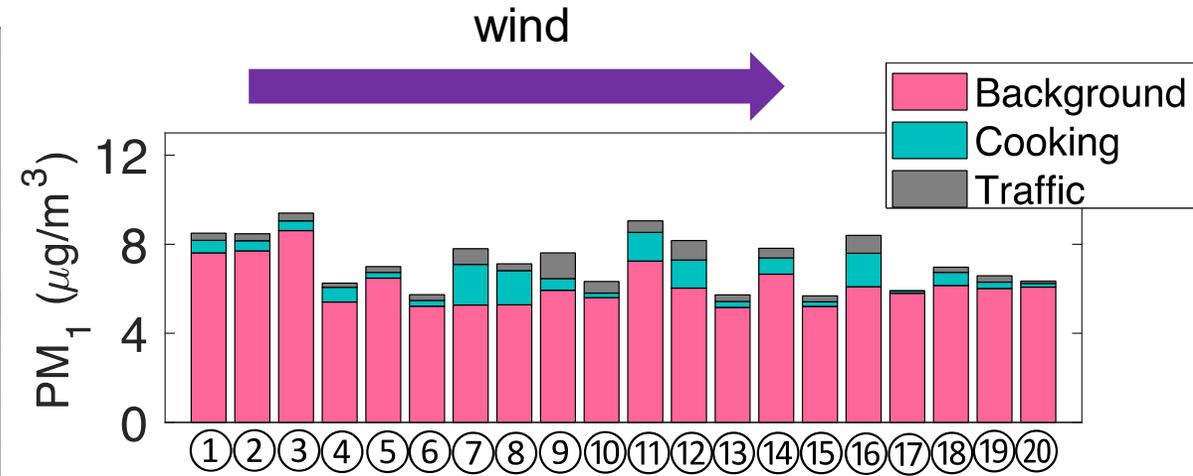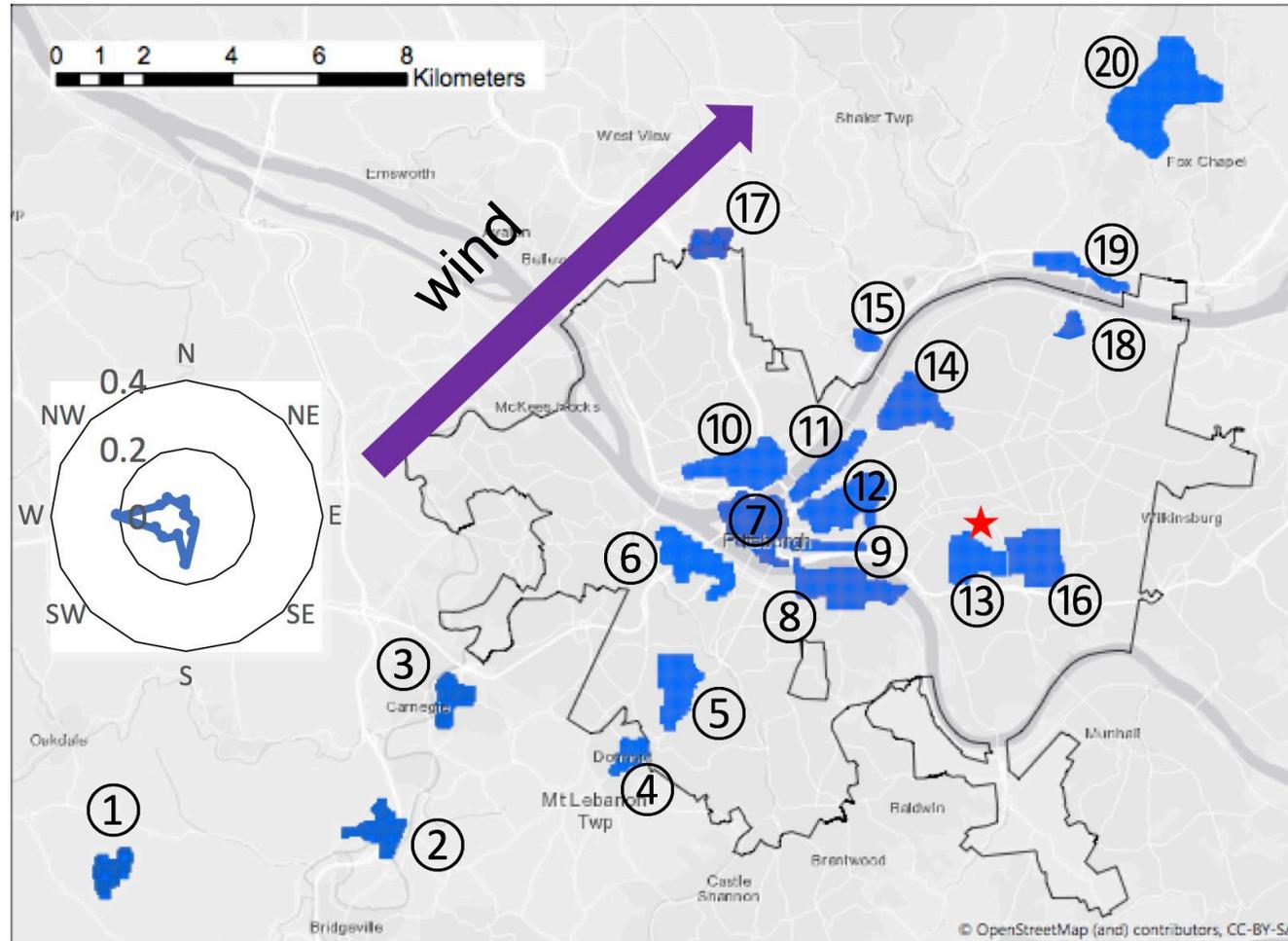

Single-particle mass spectrometer
- Bulk PM_1 mass and composition
- Individual particle's size and composition
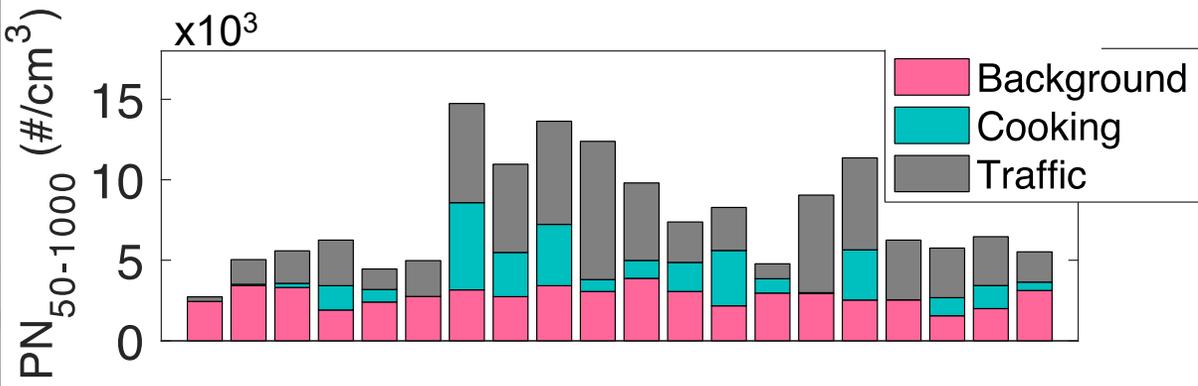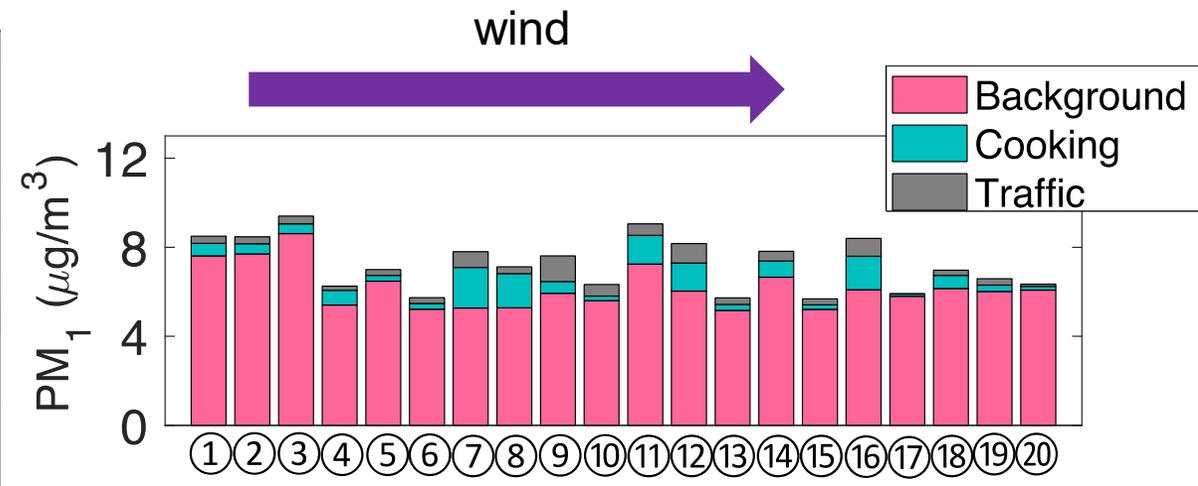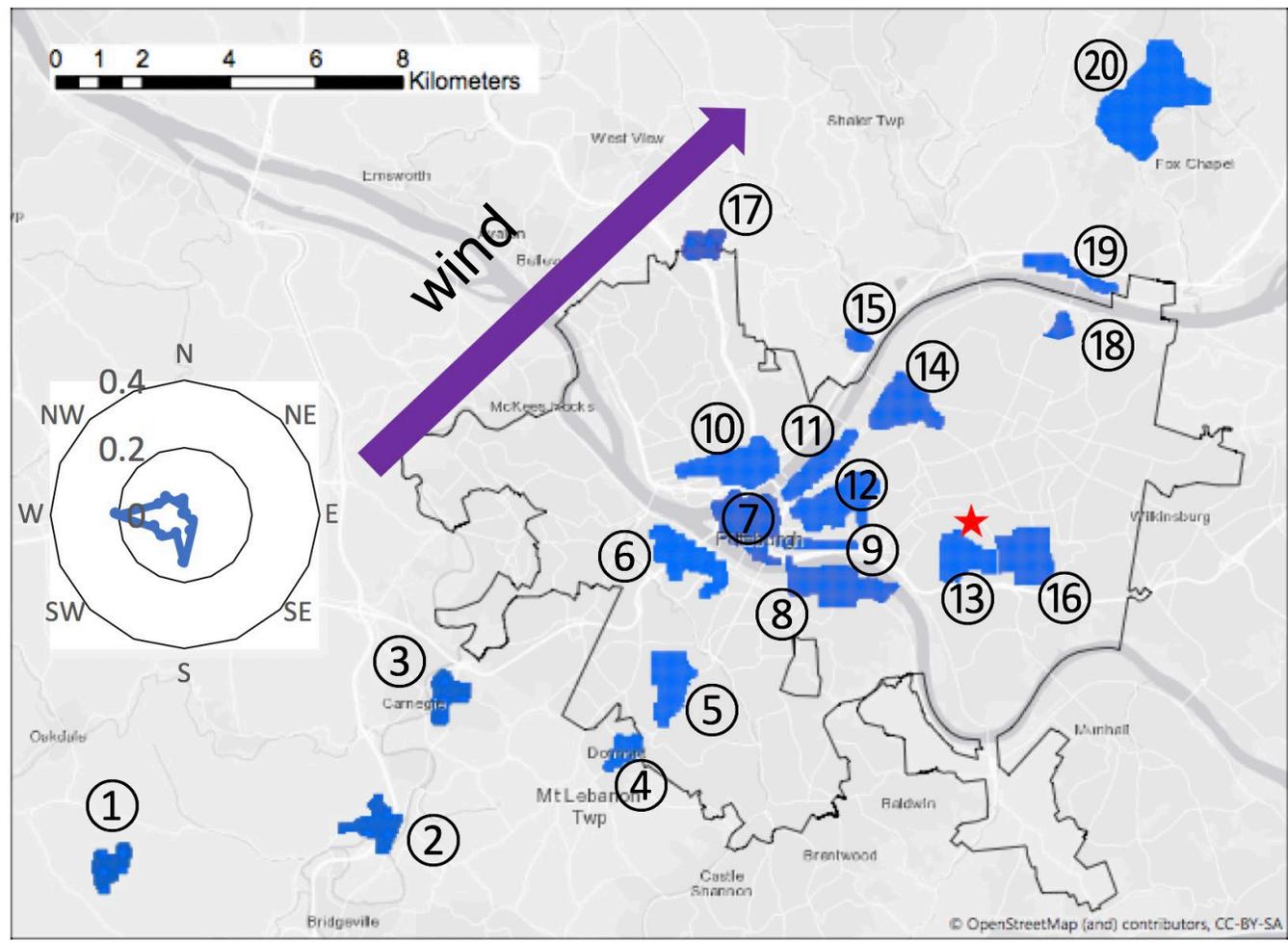- Count individual particles (50-1000nm)

ion fragments of particles → source ⎰ Background / Traffic / Cooking

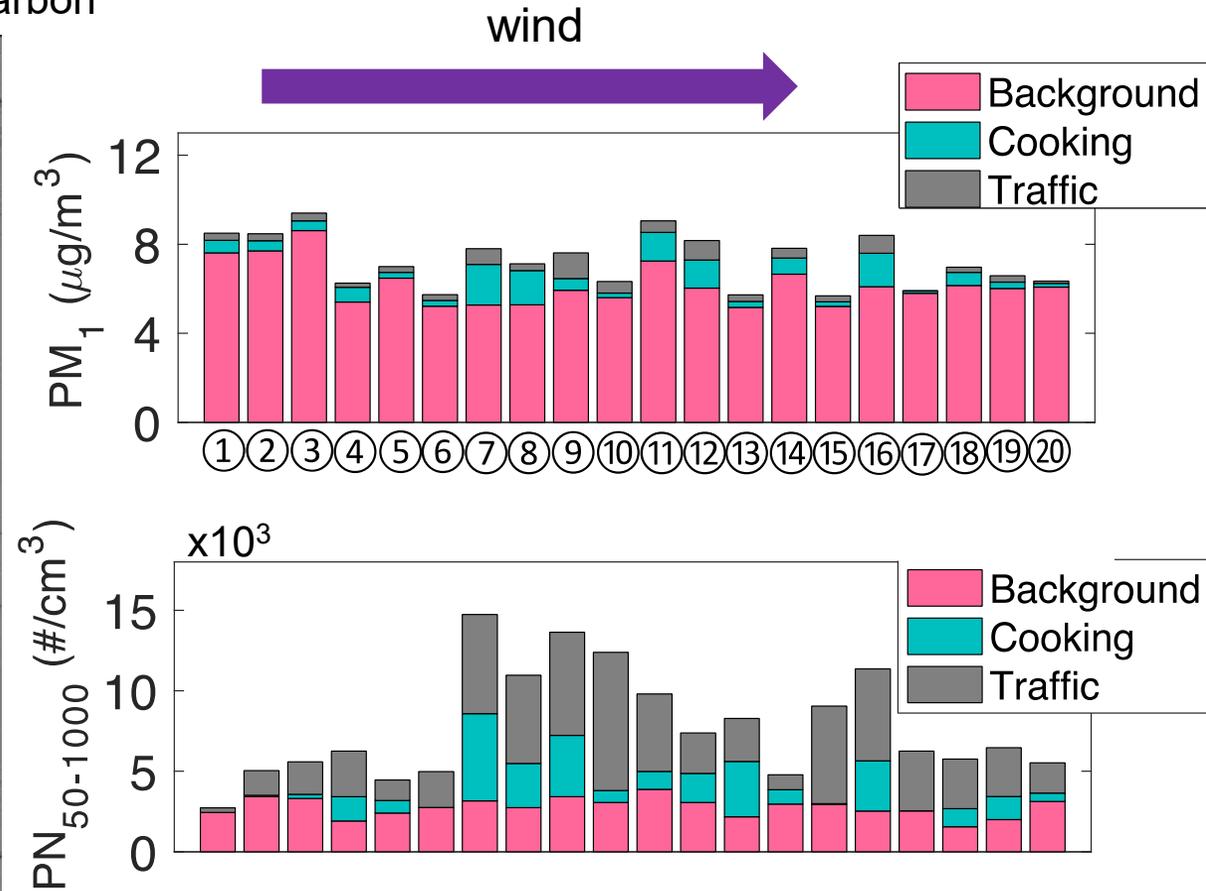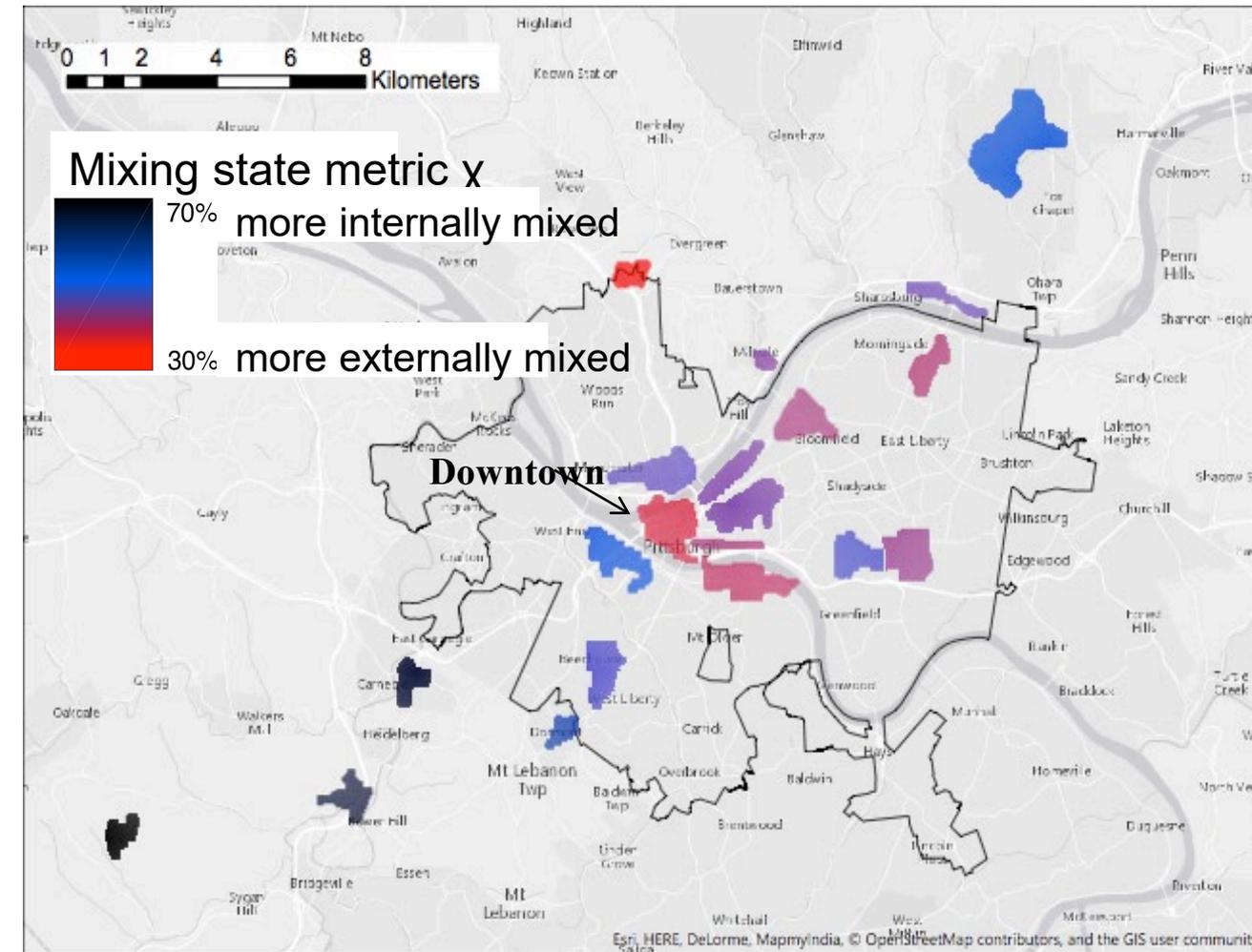# Total mass concentration is relatively uniform

# Total mass concentration is relatively uniform, but number concentration varies drastically

Urban emissions also affect particle mixing state (i.e. distribution of chemical species within a particle population)

Chemical species include organics, nitrate, sulfate, chloride, black carbon
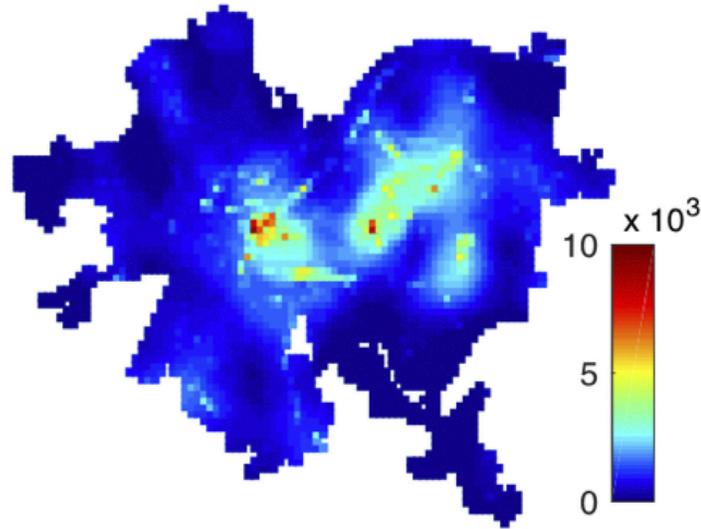
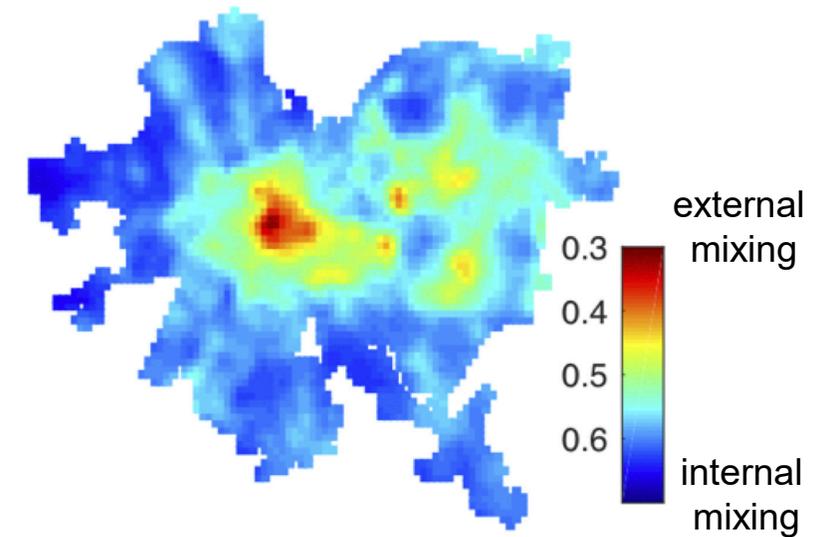# Land-use regression modeling to predict source-resolved particle number concentration and mixing state

A Traffic particles N$_{50-1000}$
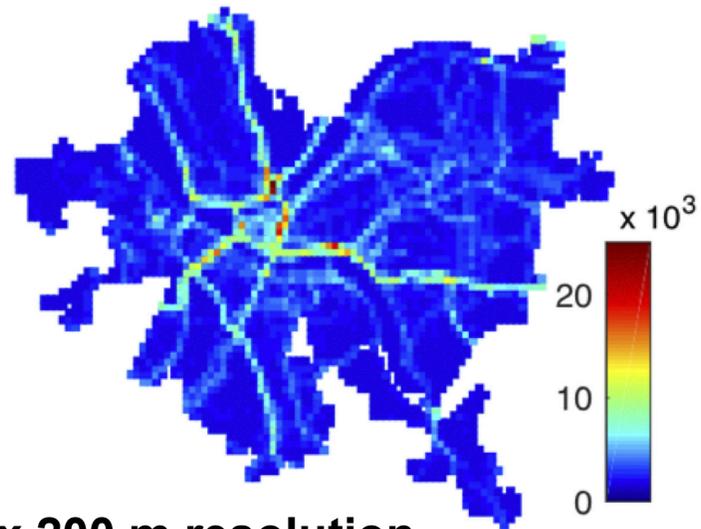
B Cooking particles N$_{50-1000}$

C Mixing state χ

200 m x 200 m resolution

| Covariates selected[a]	Coefficient	Partial R^2
Traffic	—	—
Vehicle density in all roads (100 m)	21.48	0.37
Diesel annual average daily travel × squared inverse distance to the nearest road (100 m)	321.5	0.21
Intercept	1,577	—
	total R^2: 0.58	

Covariates selected[a]	Coefficient	Partial R^2
Cooking	—	—
Restaurant counts (100 m)	12.87	0.37
Major road length (1,000 m)	0.0505	0.24
Population density (1,000 m)	0.1633	0.06
Intercept	−717.8	—
	total R^2: 0.67	

| Covariates selected[a]	Coefficient	Partial R^2
Mixing State $(1 − \chi)$, unitless	—	—
Major road length (1,000 m)	5.77×10^{-6}	0.54
House density (300 m)	7.59×10^{-5}	0.06
NEI point source density (30 km)	9.44	0.03
Intercept	−0.304	—
	total R^2: 0.63	

8

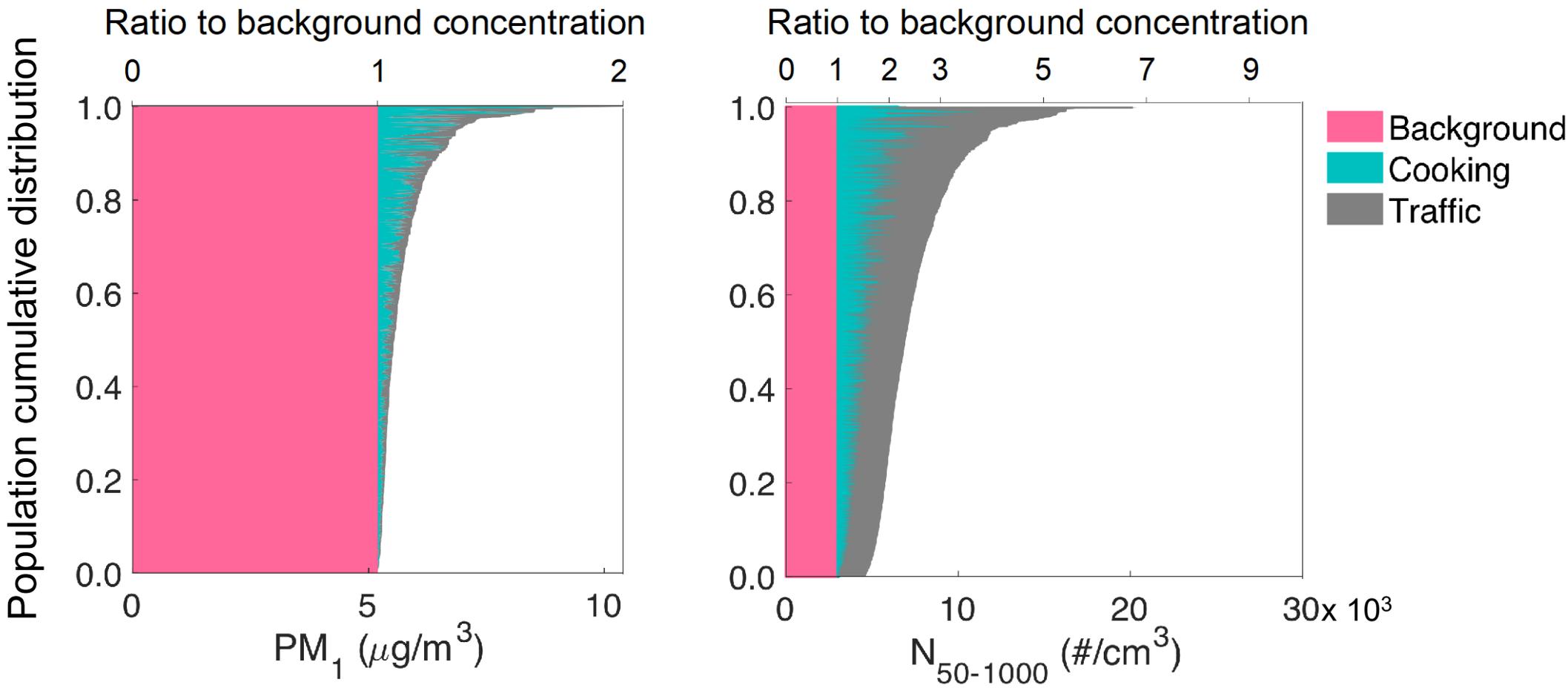# Mass exposure includes uniform background particles
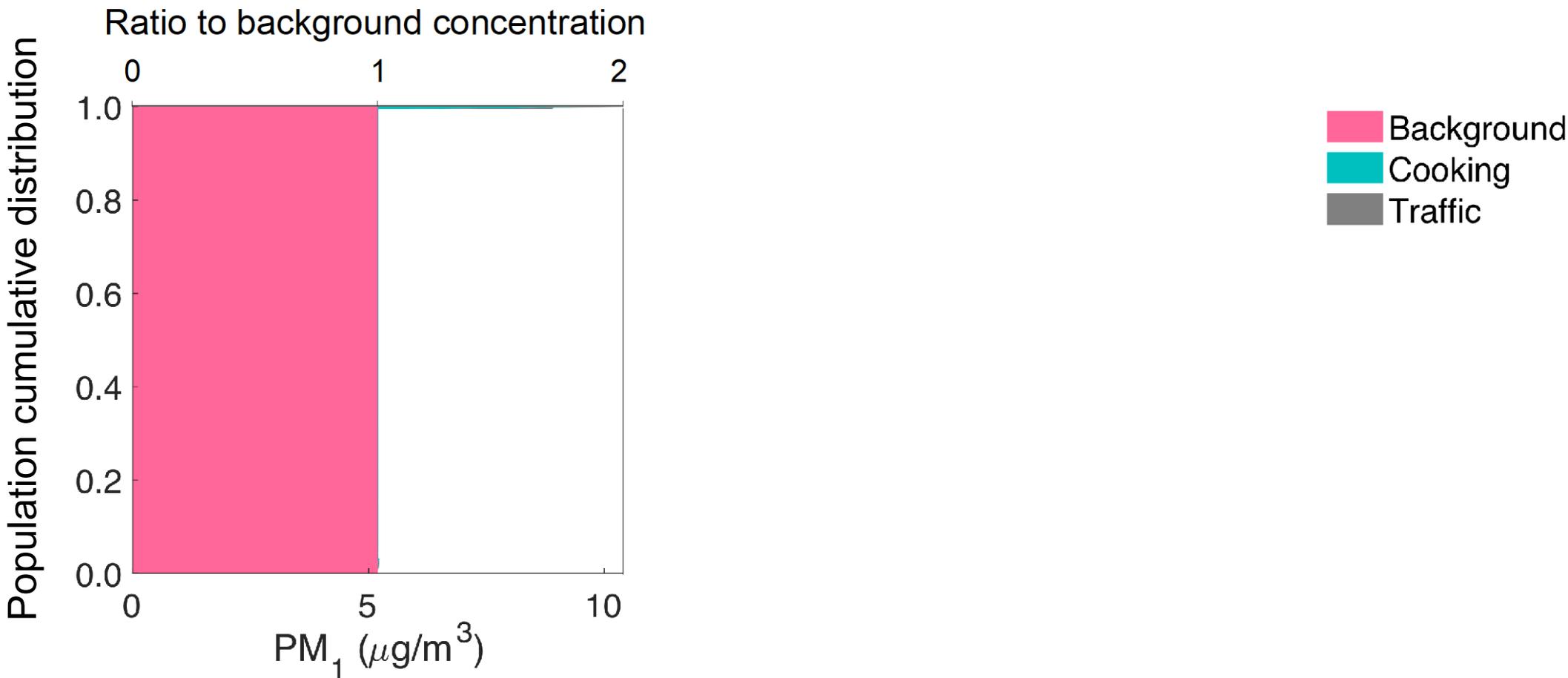
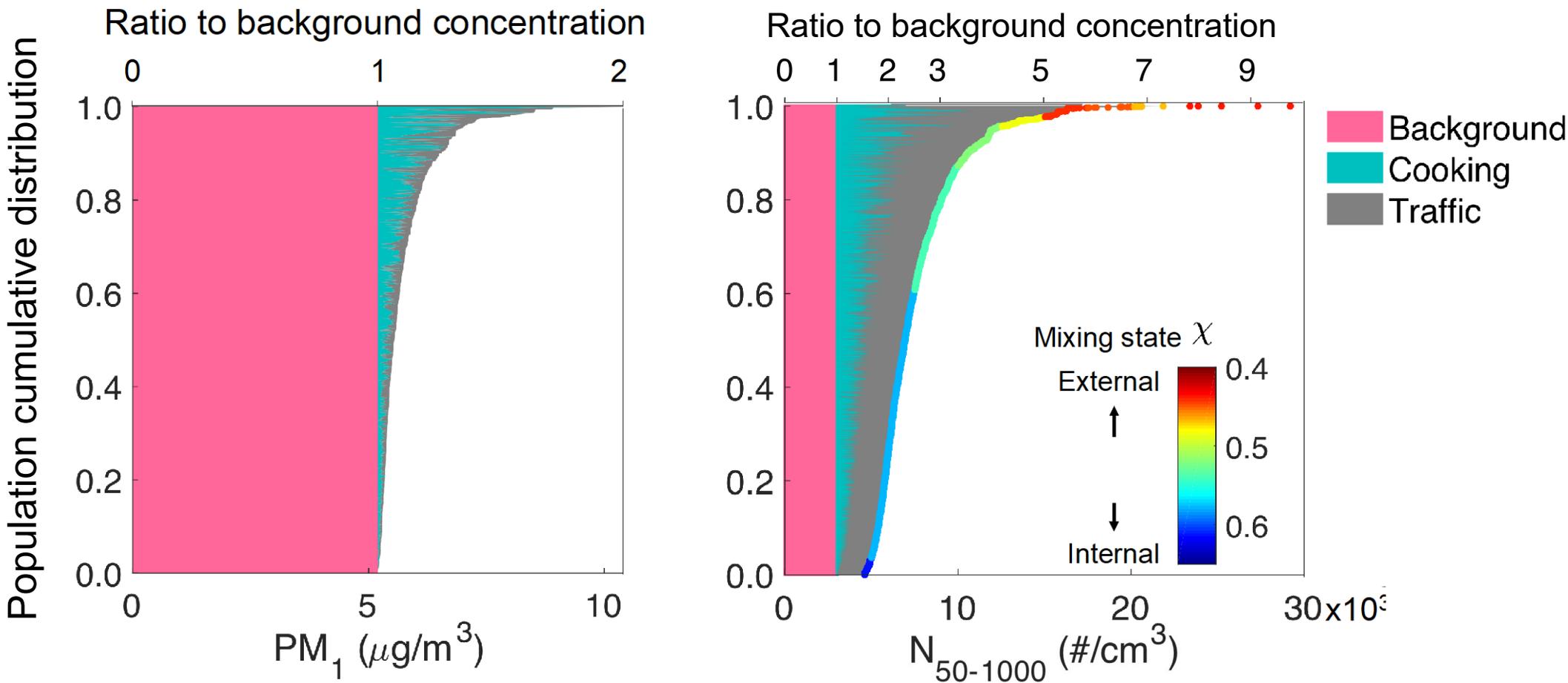# Mass exposure is dominated by background particles
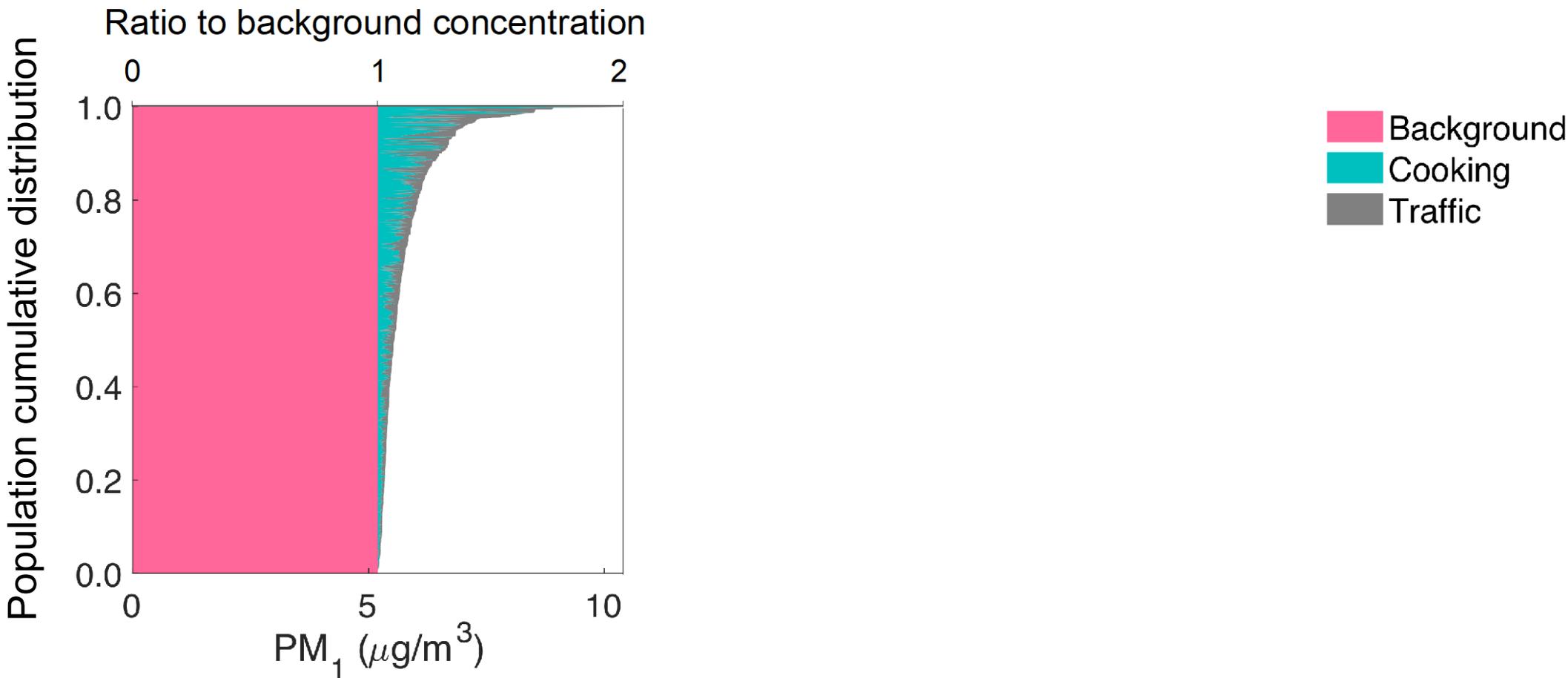
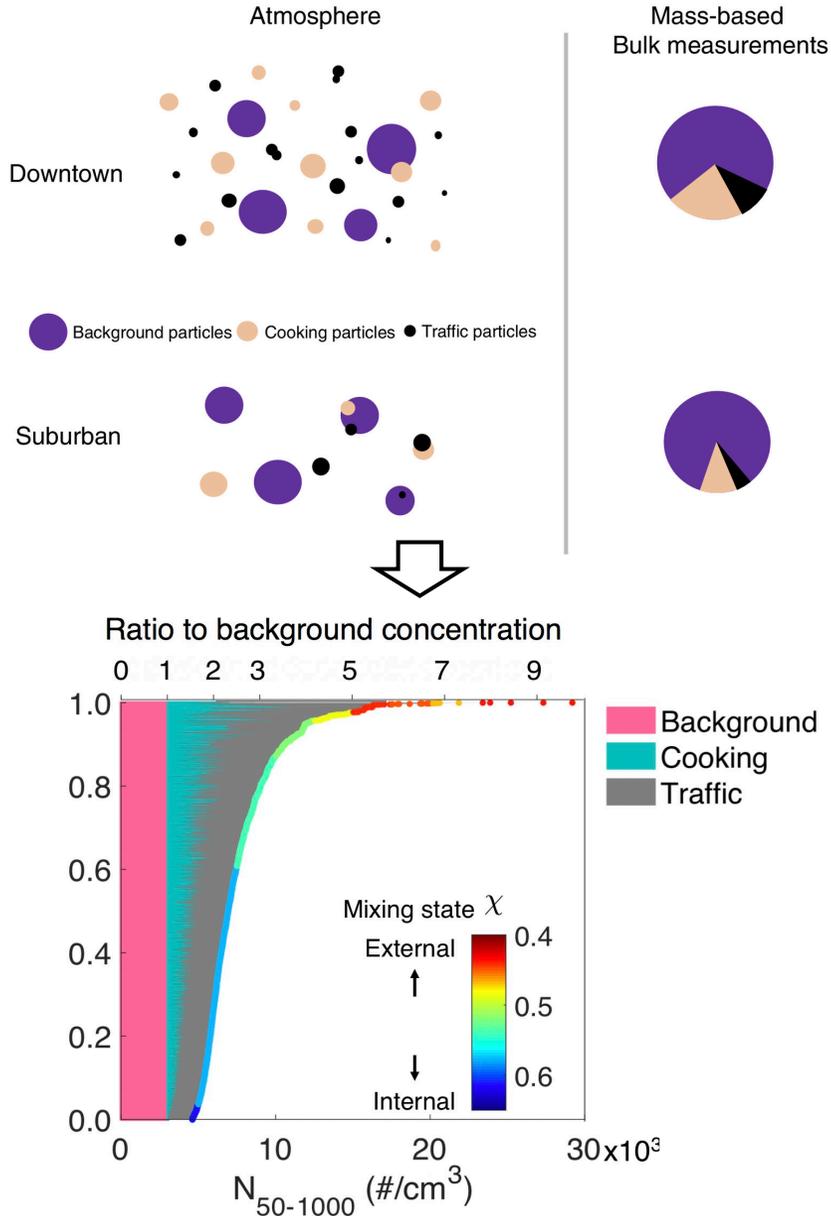# Number exposure also includes relatively uniform background particles
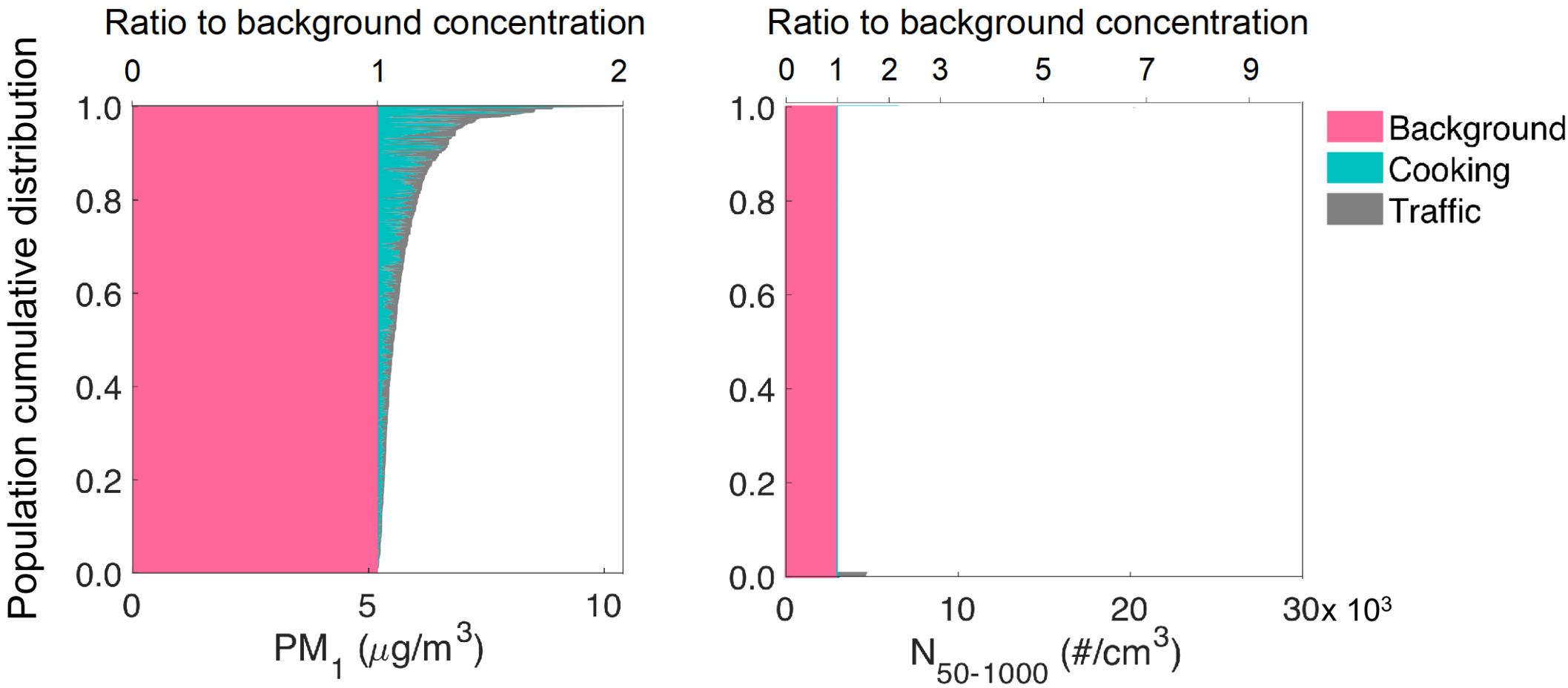
Number exposure is dominated by primary particles with high variability

High concentration exposure also correlates with external mixing

Conclusions