Within-city variation in ambient carbon monoxide concentrations: Leveraging low-cost monitors in a spatiotemporal modeling framework

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Background

- Carbon monoxide (CO) is one of the six principal air pollutants regulated under NAAQS. Anthropogenic CO is mainly generated from incomplete combustion of carbon fuels from on-road and off-road mobile sources. Wildfires have recently played a significant role in CO emissions.
- Ground-level CO concentrations have traditionally been measured at regulatory air quality stations (*e.g.*, Air Quality System/AQS). **Low-cost air monitors** and **satellite remote sensing** instruments are promising novel platforms for larger-scale, higher-resolution spatiotemporal CO measurement.
- Evidence regarding associations between long- or short-term exposure to ambient CO has been limited. The **lack of spatiotemporally high-resolution CO exposure data** is a major impediment to extensive epidemiologic analysis of the effects of CO.
- In this study, **we aimed to develop a daily, high-resolution ambient CO prediction model at the city level in Baltimore, Maryland.**

Data and Methods

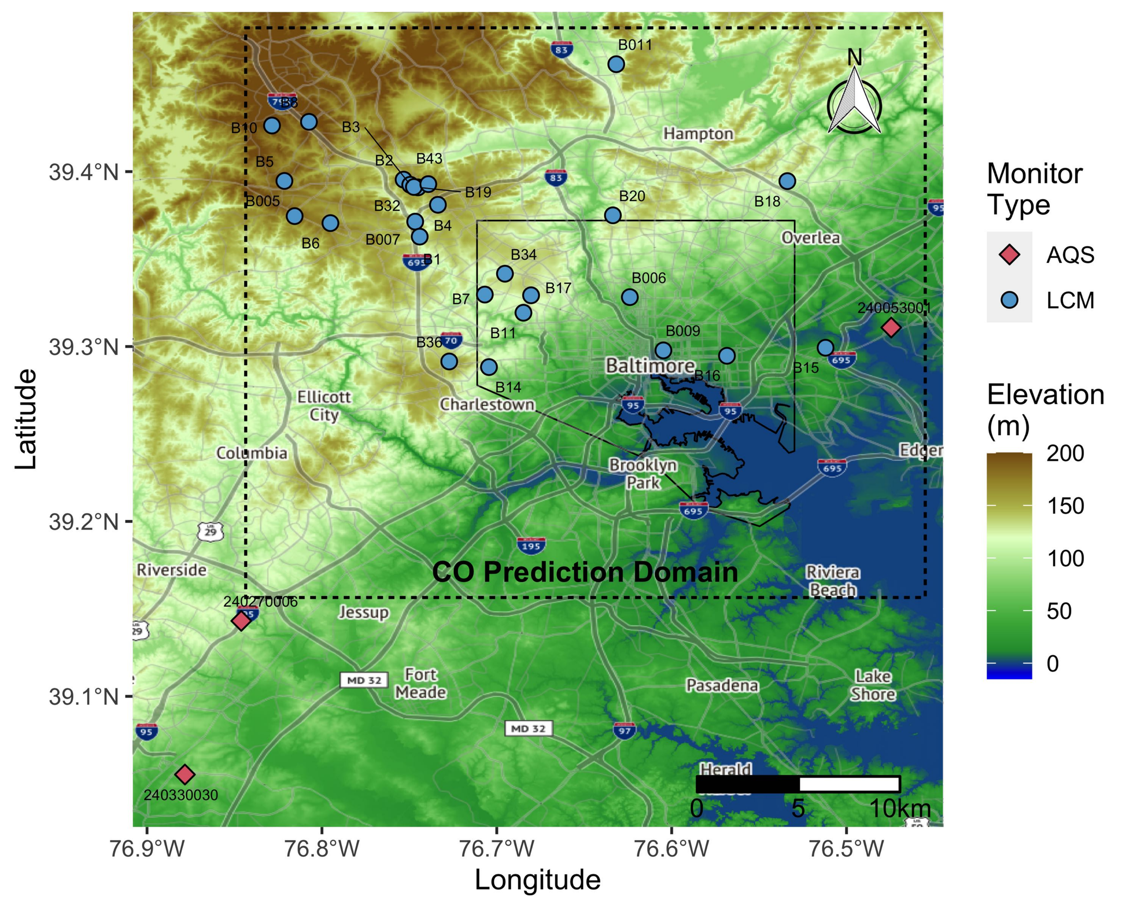

Fig 1. Study domain with locations of regulatory AQS stations and low-cost monitors (LCMs) for ambient CO measurement. The dashed line shows a sub-domain within which daily-level ambient CO concentration predictions were made. The solid line shows the boundary of Baltimore City.

AQS U.S. Environmental Protection Agency Air Quality System, a nationwide regulatory air quality monitoring network (N = 3).

LCM Monitors designed, constructed, and calibrated in a custom research application configuration fabricated at the University of Washington (N = 26).

Prediction Models We utilized a hierarchical spatiotemporal (ST) modeling framework developed previously to accommodate air pollution exposure prediction for MESA Air.

ST Modeling Framework

$$y(s,t) = \mu(s,t) + \nu(s,t)$$
$$\mu(s,t) = \sum \gamma M(s,t) + \sum \beta(s) f(t) + \beta_0(s)$$
$$\beta(s) \sim N[\mathbf{X}(s)\alpha, \textstyle\sum(\phi, \sigma, \tau)]$$

- **Baseline**: Only geographic covariates as predictors
- **Meteorology**: Geo-covariates and High-Resolution Rapid Refresh (HRRR) meteorological variables
- **Satellite**: Geo-covariates and the TROPOspheric Monitoring Instrument (TROPOMI) CO retrievals
- **Co-pollution**: Geo-covariates and co-pollutant ($PM_{2.5}$, NO_2, and NO_x) predictions

Table 1. Selected informative geographic covariates (buffer and distance to nearest object)

Road	Emission
Population	Vegetation
Land-Use	Imperviousness
Facility & Others	Elevation

Implications

- We showed that densely deployed low-cost monitors enabled reasonable characterization of CO concentration distribution, which **would be impossible** when relying solely upon spatially sparse agency monitors that missed important aspects of the distribution.
- Our CO predictions demonstrated **a tangible improvement** in terms of spatial resolution when compared to satellite products.
- The integration of high-resolution meteorological data, satellite-retrieved CO column densities, and co-pollutant ($PM_{2.5}$, NO_2, and NO_x) concentrations **did not meaningfully improve** our model's spatial or temporal predictive performance.

Modeling Results

Table 2. Leave-one-monitor-out spatial and temporal cross-validation (CV) performance of CO models built with different covariates: 1) baseline, 2) meteorology, 3) satellite, and 4) co-pollution.

Model Type	Configuration	Spatial CV		Temporal CV	
		R^2	RMSE (ppm)	R^2	RMSE (ppm)
Baseline	Three time bases; Four principal components (1, 2, 7, &, 12)	0.70	0.02	0.61	0.04
Meteorology		0.70	0.02	0.63	0.04
Satellite		0.64	0.03	0.64	0.04
Co-Pollution		0.39	0.03	0.57	0.04

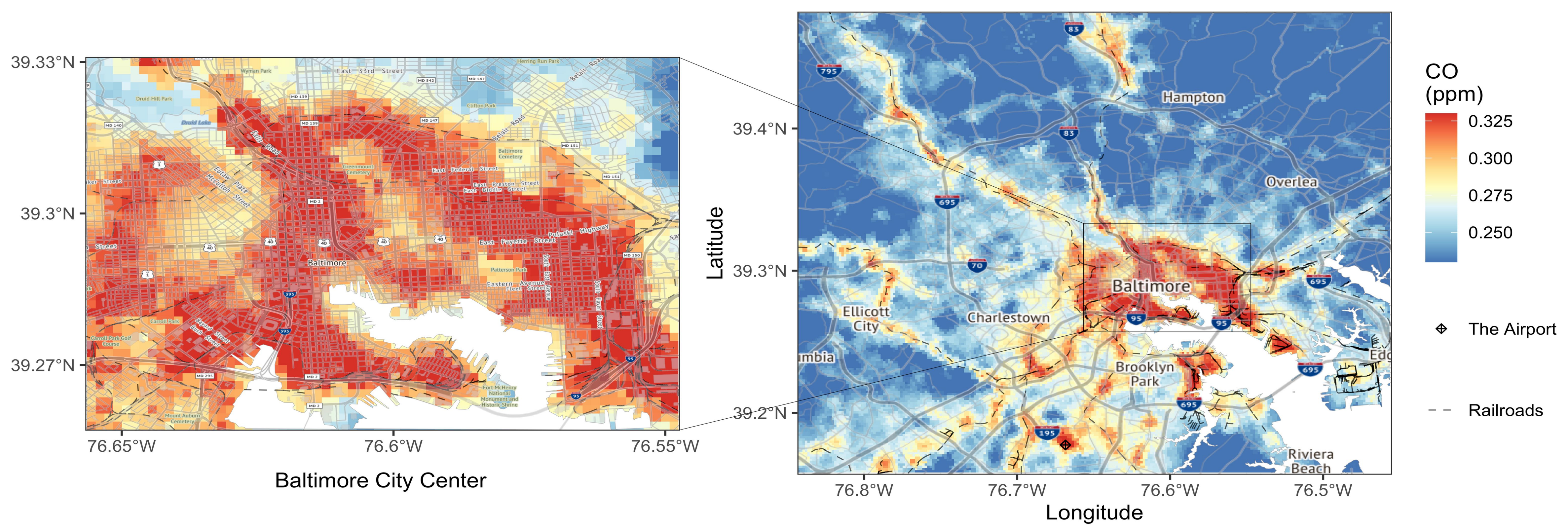

Fig 2. Annual mean CO prediction distributions from the baseline model in 2018 at a 200-m resolution.

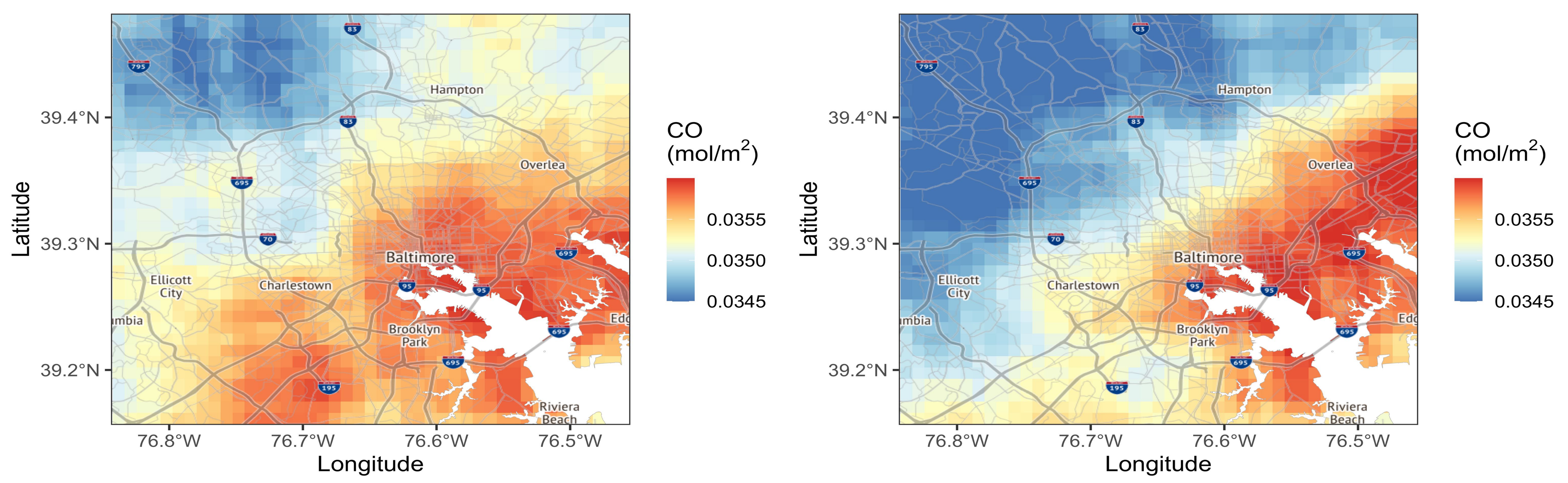

Fig 3. Annual mean TROPOMI CO column densities in 2019 (left) and 2020 (right) at a 1-km resolution.

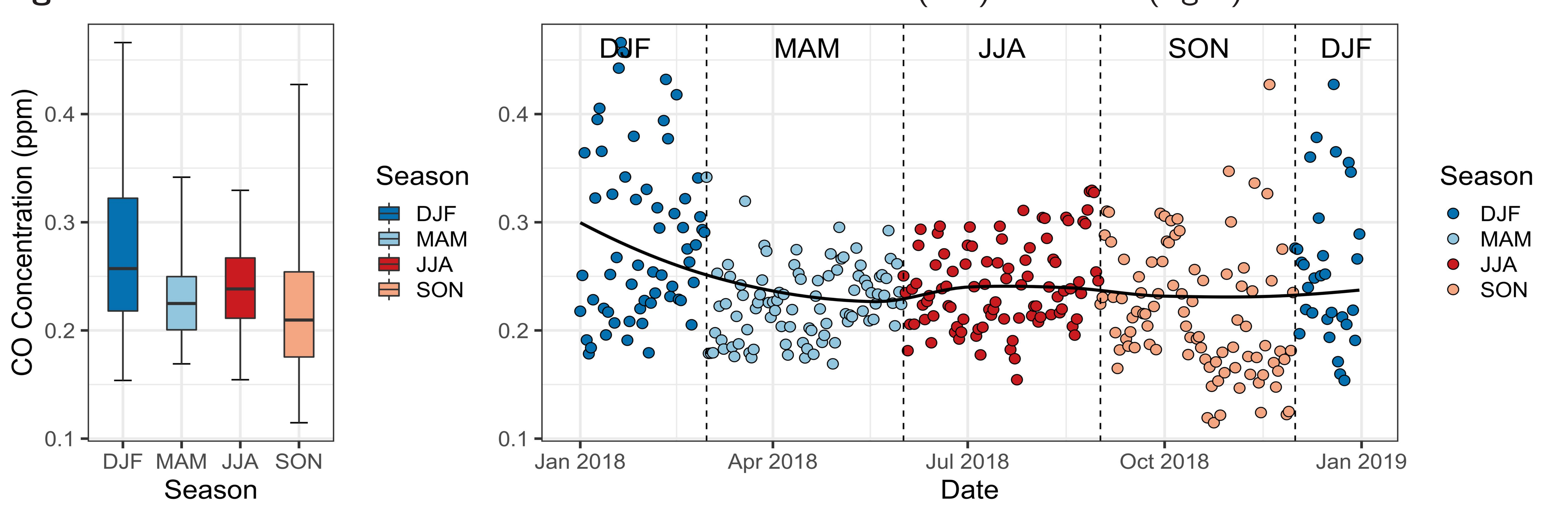

Fig 4. Domain-wide, daily-level temporal variations of CO concentrations from the baseline model.

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