Incorporating Low-Cost Sensor Measurements into High-Resolution $PM_{2.5}$ Modeling at a Large Spatial Scale

Jianzhao Bi[1], Avani Wildani[2], Howard H. Chang[3], Yang Liu[*,1]

[1] Department of Environmental Health, Emory University, Rollins School of Public Health, Atlanta, GA, USA
[2] Department of Computer Science, Emory University, Atlanta, GA, USA
[3] Department of Biostatistics and Bioinformatics, Emory University, Rollins School of Public Health, Atlanta, GA, USA
[*] Mailing Address: 1518 Clifton Road NE, Atlanta, GA 30322, USA. E-mail: yang.liu@emory.edu.

Background

Fine particulate matter ($PM_{2.5}$) is associated with a broad range of adverse health outcomes. Ambient $PM_{2.5}$ exposure assessment has traditionally relied on sparse regulatory air quality monitoring stations. Emerging low-cost air quality sensors (<$2,500) have desirable features such as flexibility of deployment and ease of maintenance. However, there are two major limitations with regard to using a low-cost sensor network to improve $PM_{2.5}$ pollution mapping and exposure assessment. **First**, due to the significant cost of extensive field testing by trained scientists, the side-by-side low-cost sensor calibration against reference-grade monitors has mostly been confined in a small region. **Secondly**, even though low-cost sensor data can have a relatively low systematic bias after calibration, their precision is still not comparable to reference-grade measurements. In this study, we conducted **a spatially varying calibration** and developed **a down-weighting strategy** to integrate low-cost sensor data (***PurpleAir***) with regulatory data (Air Quality System, ***AQS***) into high-resolution $PM_{2.5}$ modeling in California.

Data and Methods

Large-Scale PurpleAir Calibration

* PurpleAir sensors were paired with the nearest AQS stations within a 500-m radius (26 paired AQS/PurpleAir sites in California)
* A Geographically Weighted Regression (GWR) model with temperature, humidity, PurpleAir sensor operational time for the calibration

GWR Calibration Model

$$\text{AQS PM}_{2.5} = \beta_0 + \beta_1 \cdot \text{PurpleAir PM}_{2.5} + \beta_2 \cdot \text{T} + \beta_3 \cdot \text{RH} + \beta_4 \cdot \text{Opl.Time}$$

Weighted $PM_{2.5}$ Modeling

* PurpleAir Weights
  - A reference weight for AQS, $\mathbf{w_{AQS} = 1}$
  - Lower weights for PurpleAir, $\mathbf{w_{PA} \in (0, 1)}$
    - σ^2: Errors of prediction model structure
    - τ^2: Residual errors of PurpleAir
    - ρ: A data-driven scale factor

PurpleAir Weights: $\text{w}_{\text{PA}} = \rho \cdot \frac{\sigma^2}{\sigma^2 + \tau^2}$

* The Random Forest Prediction Model
  - **Dependent Variable:** AQS and PurpleAir $PM_{2.5}$ data with different weights
  - **Predictors:** Satellite aerosol optical depth (AOD), meteorological, and land-use data
  - 1-km, daily $PM_{2.5}$ predictions were generated

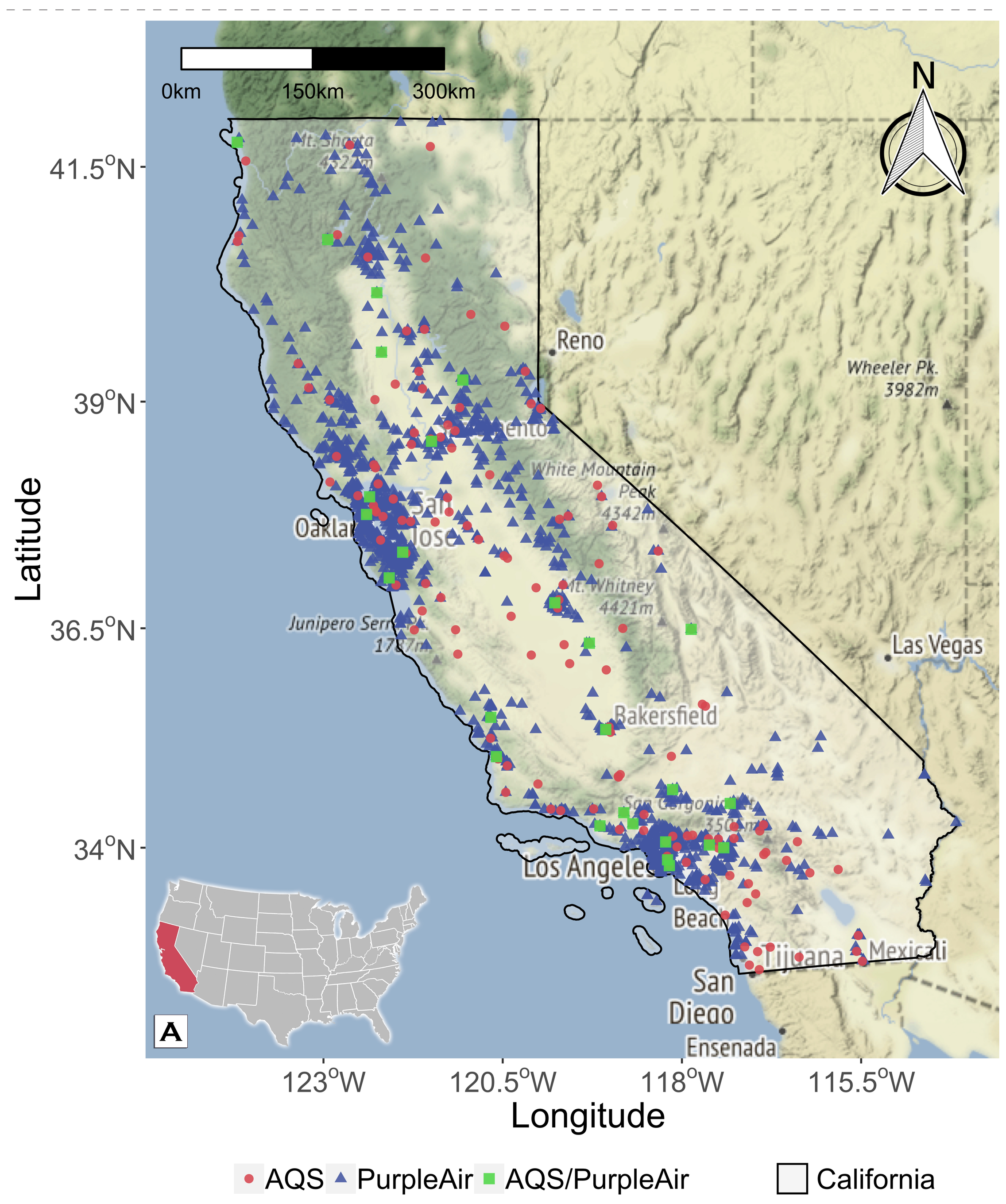

Fig 1. Study domain, California, with 157 AQS, 2,090 PurpleAir, and 26 paired AQS/PurpleAir sites.

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Implications

* For a region with the size of California, at least ~20 well-distributed, continuous reference-grade monitors, *i.e.*, ~**5 stations per 100,000 km²**, are needed to effectively calibrate PurpleAir data.
* The negative impact of the large uncertainty in low-cost sensor data can be mitigated by down-weighted modeling to better take advantage of their high spatiotemporal frequency in $PM_{2.5}$ estimation.
* The two-step low-cost sensor data integration framework (calibration and down-weighting) can be **generalized to other regions** with limited regulatory monitors to advance $PM_{2.5}$ exposure assessment.
* The proposed framework can even be **transferred to other citizen science applications**, such as meteorological, geographical, and ecological citizen science programs, to combine a large volume of low-quality volunteer-generated data and few gold-standard scientific data.

Weighted $PM_{2.5}$ Modeling

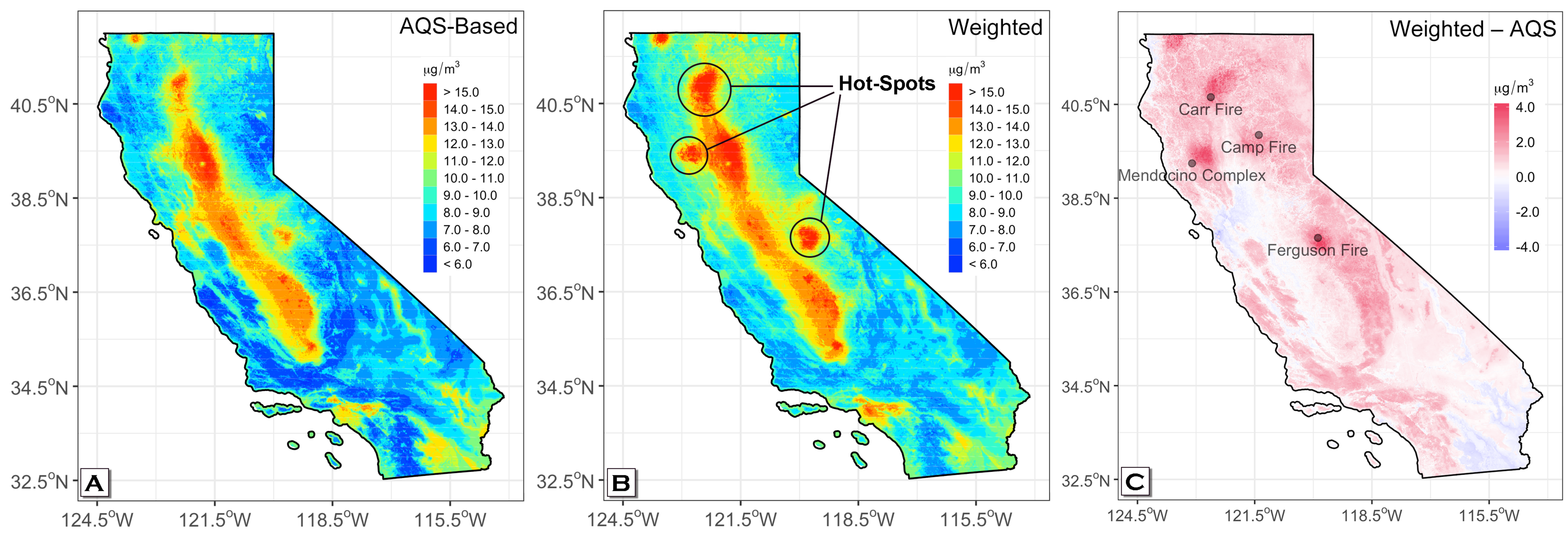

Fig 2. (A) – (B): Annual mean $PM_{2.5}$ distributions for the year of 2018 derived by (A) the AQS-based model and (B) the weighted model. (C): Annual mean $PM_{2.5}$ differences between the weighted and AQS-based models (weighted minus AQS-based) with the locations of the four most destructive wildfires in California in 2018.

Table 1. Cross-validation performance of the prediction models. CV was only performed on AQS measurements not used in calibrating PurpleAir (N = 32,981).

Model	Random CV R^2	Spatial CV R^2	Temporal CV R^2	CV RMSPE ($\mu g/m^3$)
The AQS-Based Model	0.83	0.75	0.77	6.04
The Weighted Model	0.86	0.81	0.77	5.62

* The PurpleAir weights were between 0.10 to 0.17 (against the AQS weight of 1), indicating that the contribution of PurpleAir data was no more than 20% of that of AQS data in achieving the best modeling performance.
* Dense low-cost measurements showed their potential to help the prediction model better reflect $PM_{2.5}$ hot-spots such as wildfires.

Large-Scale PurpleAir Calibration

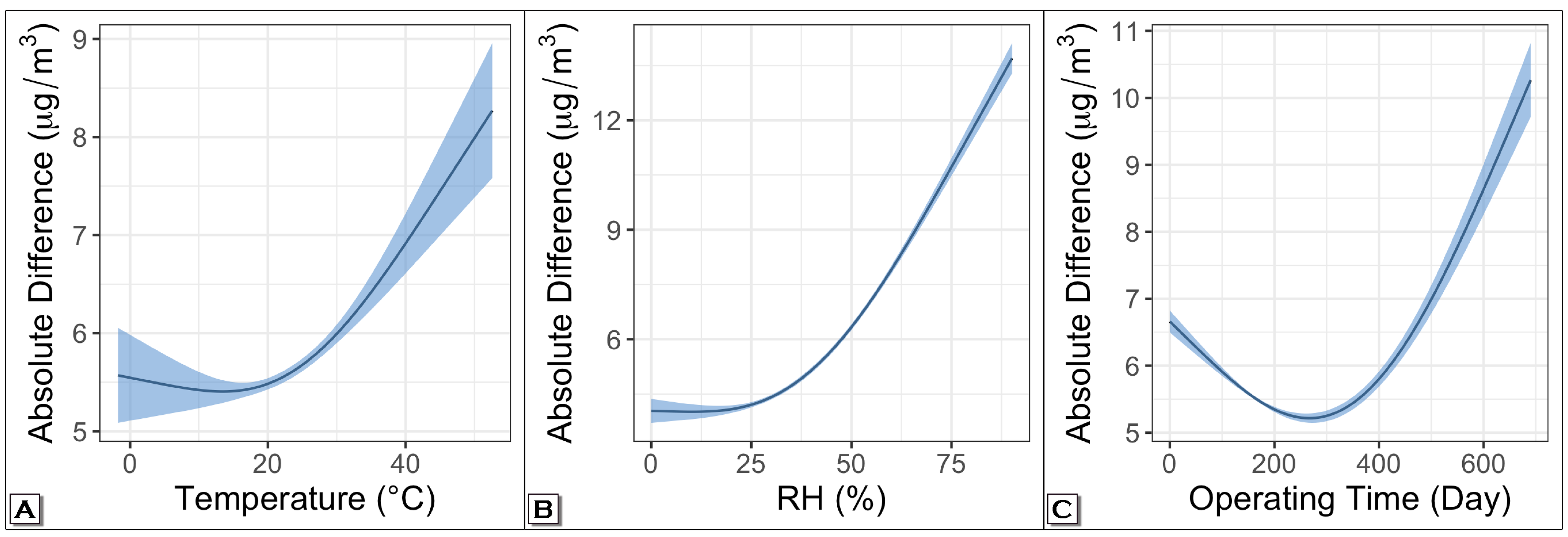

Fig 3. The nonlinear relationships with 95% confidence intervals between the absolute differences of paired AQS/PurpleAir hourly measurements and (A) temperature, (B) RH, and (C) sensor operating time.

* The calibration reduced the overall systematic bias of PurpleAir from 1.9 $\mu g/m^3$ to ~0 $\mu g/m^3$.
* The overall residual error of PurpleAir measurements was also decreased by 36%.
* Increased temperature and humidity were related to a near-exponentially increased PurpleAir data bias.
* A sensor with an operating time of 2 years tended to have a ~2-time higher bias than a sensor in 9 months.