Evaluation and modeling of data from low-cost air quality sensors for accurate $PM_{2.5}$ estimation

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Background

Motivation:

- Low-cost sensors are producing high resolution spatio-temporal data
- Low –cost sensors data can be noisy and low in accuracy[1][2] and sensitive to weather parameters
- Correction models are built to correct $PM_{2.5}$ form PurpleAir (PA) sensor data using EPA measurements as gold-standard[1][2]
- Existing models are applicable US wide and use relative humidity (RH) for correction [2]

Figure 1: PA sensor deployed for AQ measurement

Research objectives:

- Build and investigate PA $PM_{2.5}$ correction model performance as function of distance
- Evaluate the model performance based on multiple PA sensors vs single PA sensor

Methodology

- Data source: Cook county, Illinois, USA; 2019 August to 2020 July from EPA and PA
- Prediction models were built using PA-measured temperature (T) and relative humidity (RH) as correction factors
- Prediction accuracy of models built using single PA sensor and multiple PA sensor data were compared
- Determined the effect of distance between PA and EPA sites on model performance
- Identified the optimal number of PA sensors needed for accurate prediction

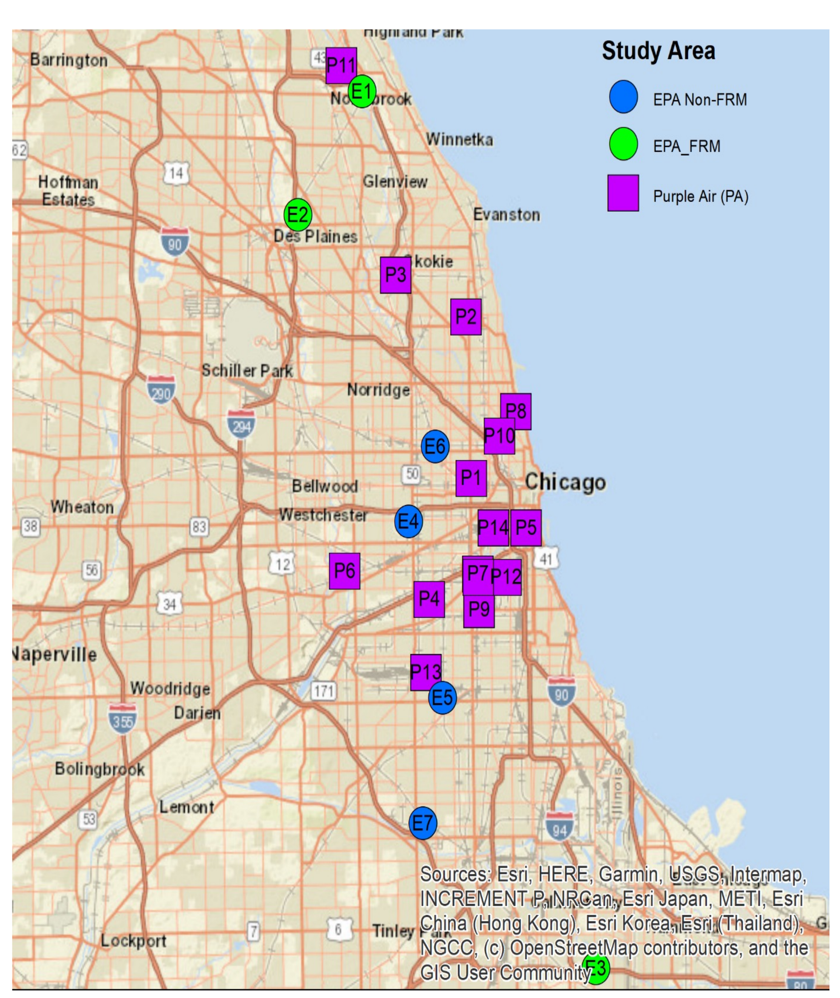


Figure 2: Location of 15 PA sensors (purple) and 7 EPA air monitoring sites including 3 FRM/FEM (green), and 4 non-FRM/FEM (blue) in Cook County, Chicago, Illinois, USA.

Results

$PM_{2.5}$ data distributions:

- Median values of $PM_{2.5}$ from PA sensors (10.9) and EPA (8.7) are shown by the dashed-lines

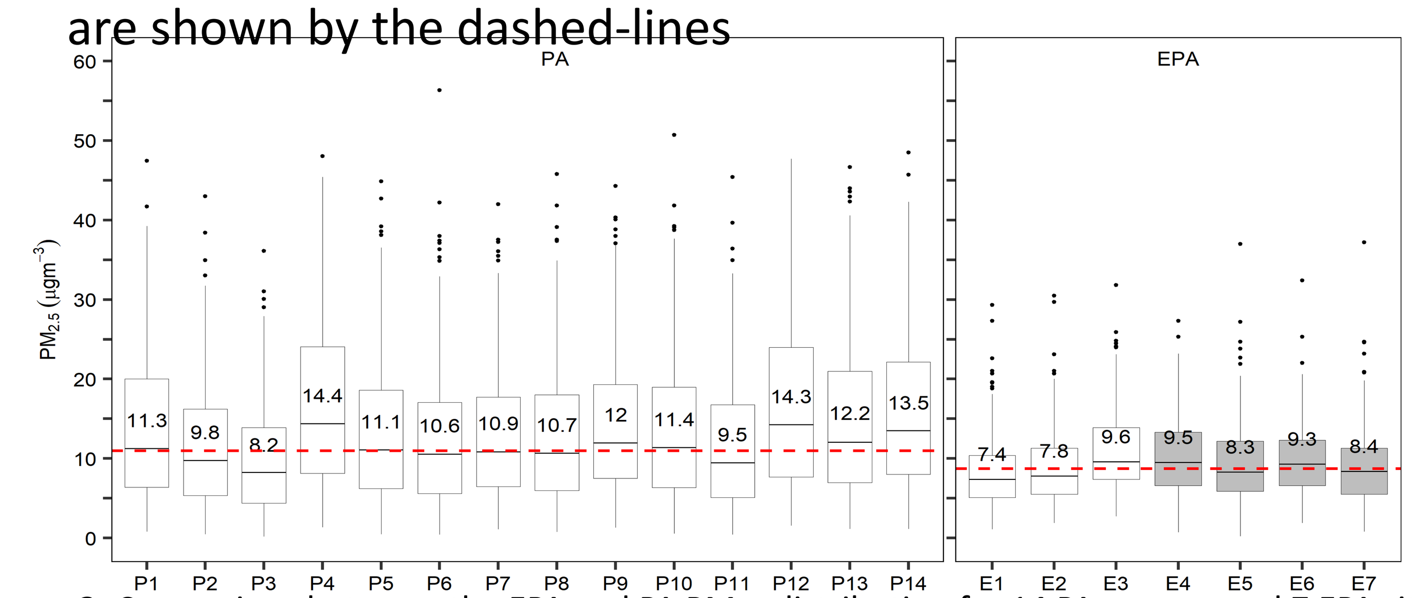


Figure 3: Comparison between the EPA and PA $PM_{2.5}$ distribution for 14 PA sensors and 7 EPA sites

Effects of temperature and relative humidity on model accuracy:

$PM_{2.5\,(EPA)} = \beta_0 + \beta_1 PM_{2.5\,(PA)} + \beta_2 RH_{(PA)} + \beta_3 T_{(PA)}$ where $\beta_2, \beta_3 = 0$ (None), $\beta_3 = 0$ (RH), $\beta_2 = 0$ (T)

- **RH** has a stronger influence in models when FRM data were used
- **T** has a stronger influence in models when non-FRM data were considered

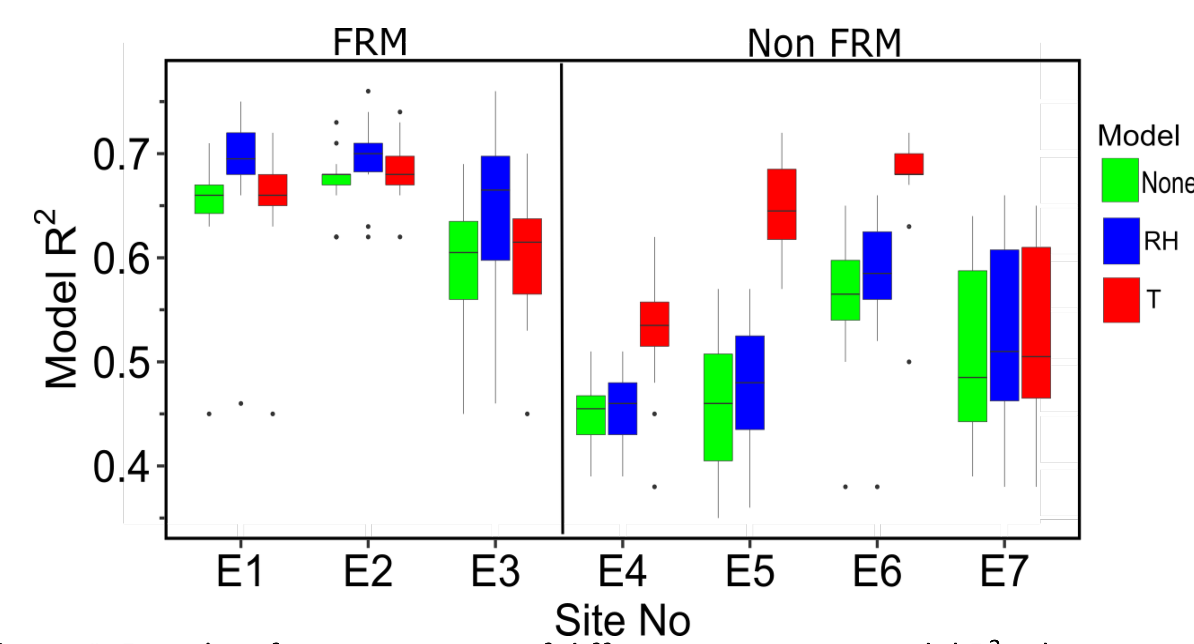


Figure 4: Box plots for comparisons of different correction model R^2 values

Effect of distance on model prediction accuracy:

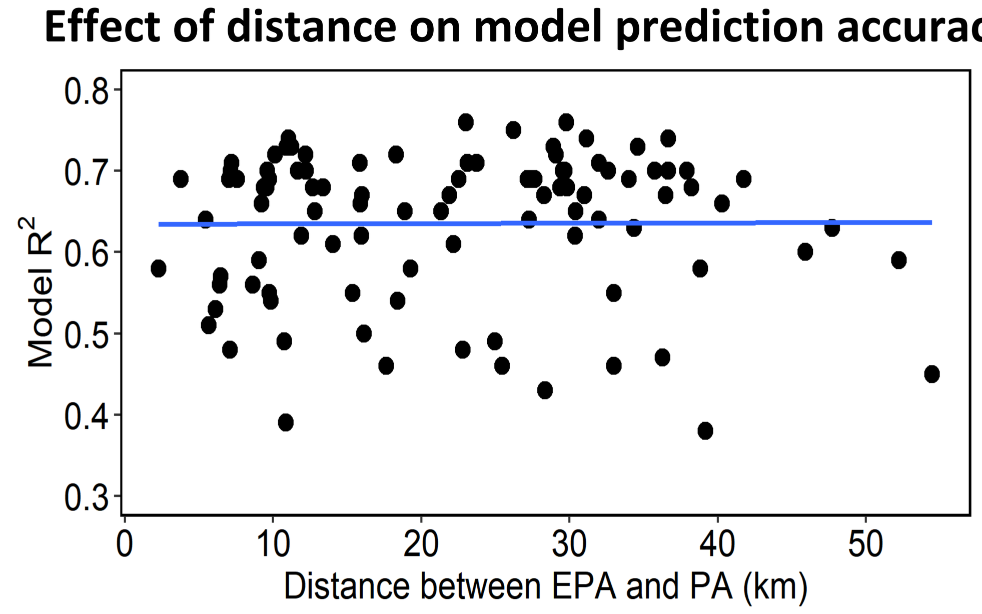


Figure 5: Model R^2 values plotted against distances between PA and EPA sites

- When consider overall, no effect from distance for the model R2 values

Changes of model accuracy across various distance groups:

- Distances were divided into 4 groups (0-10, 10-20, 20- 30 and > 30 km)
- Order restricted inference[10] applied for model R^2 with distance groups

Hypotheses

$H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4$ vs. $H_1: \mu_1 \geq \mu_2 \geq \mu_3 \geq \mu_4$

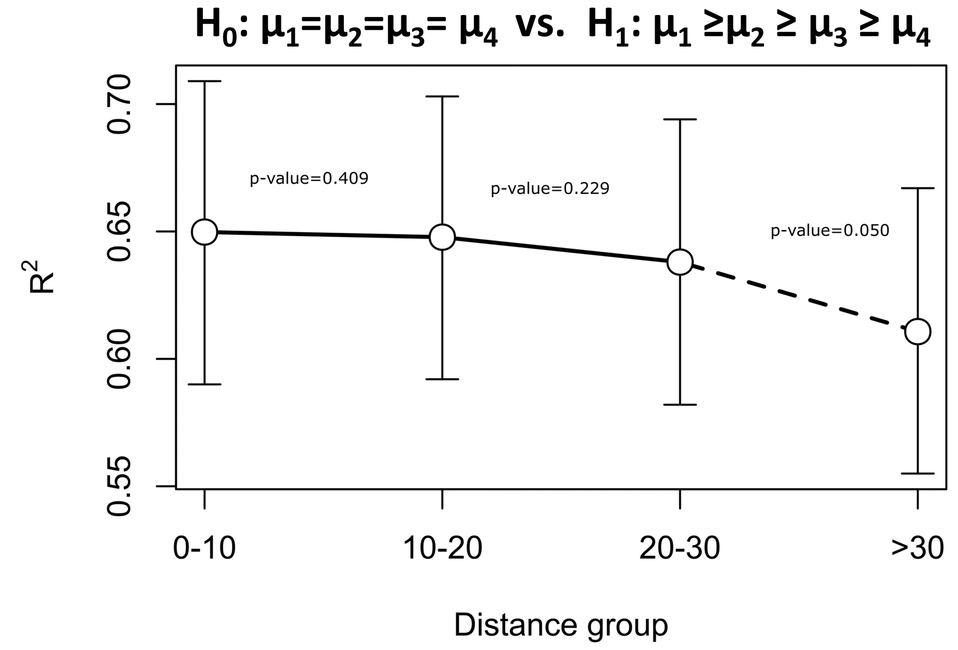


Figure 6: Plot of mean model R^2 under each distance groups

- Global test: no deceasing trend in model R^2 values were observed with increasing distances
- Pairwise analysis: model accuracy decreased for groups when distance is > 30 km

Results

Correction models built with multiple PA sensors:

$PM_{2.5\,(EPA)} = \beta_0 + \beta_1 T_{(PA)} + \beta_2 RH_{(PA)} + \sum_{i=3}^{7} \beta_i PM_{2.5\,(PAj)}$, where j = 1,..,5

- PA sensors within 30 km for each EPA site with all possible combination of 2, 3, 4, 5 PA sensors were considered
- Considering > 3 PA sensors in the model results in minimal improvement of model performance.

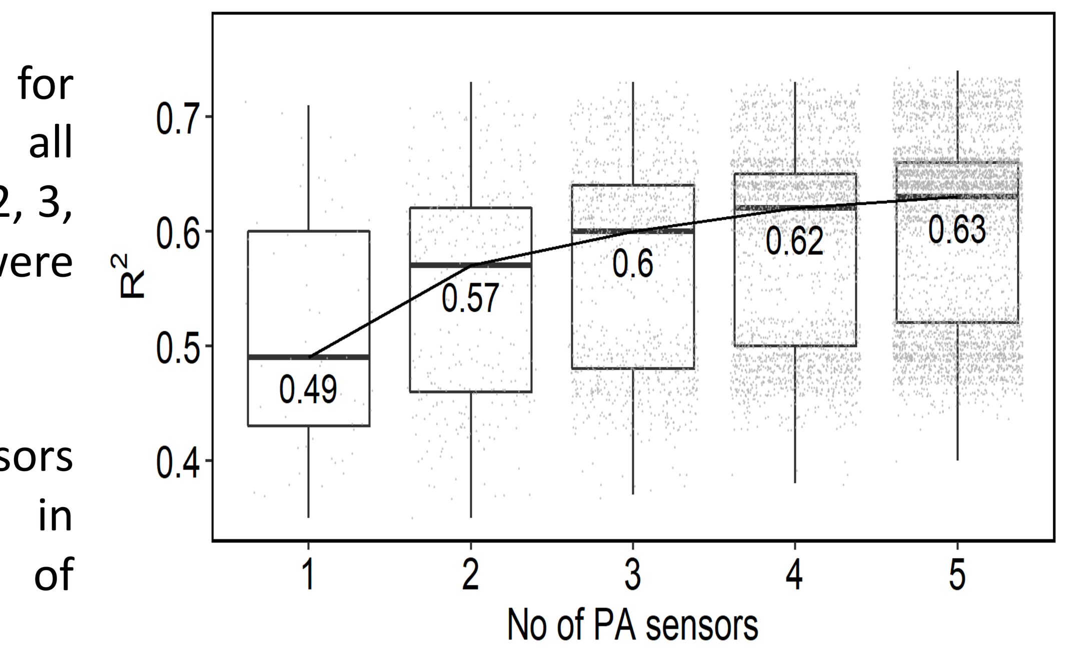
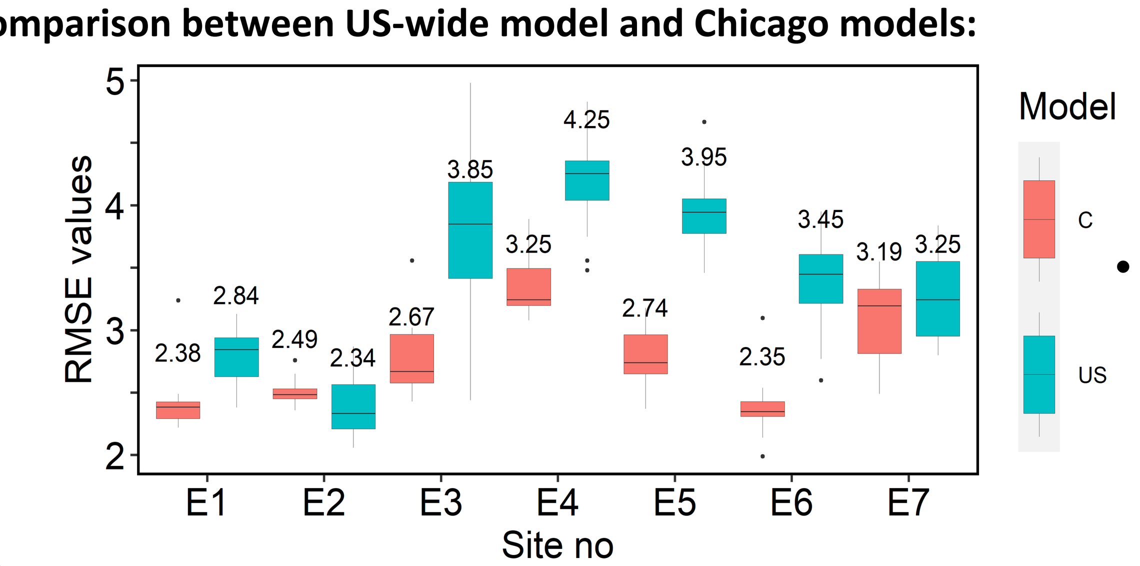


Figure 7: Box plots for multiple PA sensor model R^2 values

Comparison between US-wide model and Chicago models:



- Local models have a lower RMSE values compared with the US-wide model

Figure 8: Box plots of RMSE values for local Chicago models (C) and US-wide models (U)

Conclusion & Future work

- Relative humidity and temperature provide more accurate prediction for FRM and non-FRM data, respectively
- Model R^2 values decrease significantly when the distance between EPA and PA sensors are > 30 km
- Models using multiple PA sensors performed better than using a single PA sensor, however, improvement was minimal for more than >3 PA sensors
- Consideration of additional parameters such as wind speed and wind direction might help to obtain higher model accuracy

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