Investigating Use of Low-Cost Sensors to Increase Accuracy and Equity of Real-Time Air Quality Information

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With Rachel Nethery, Priyanka deSouza, Danielle Braun, and Leila Kamareddine

Background: air quality (AQ) data reported by countries

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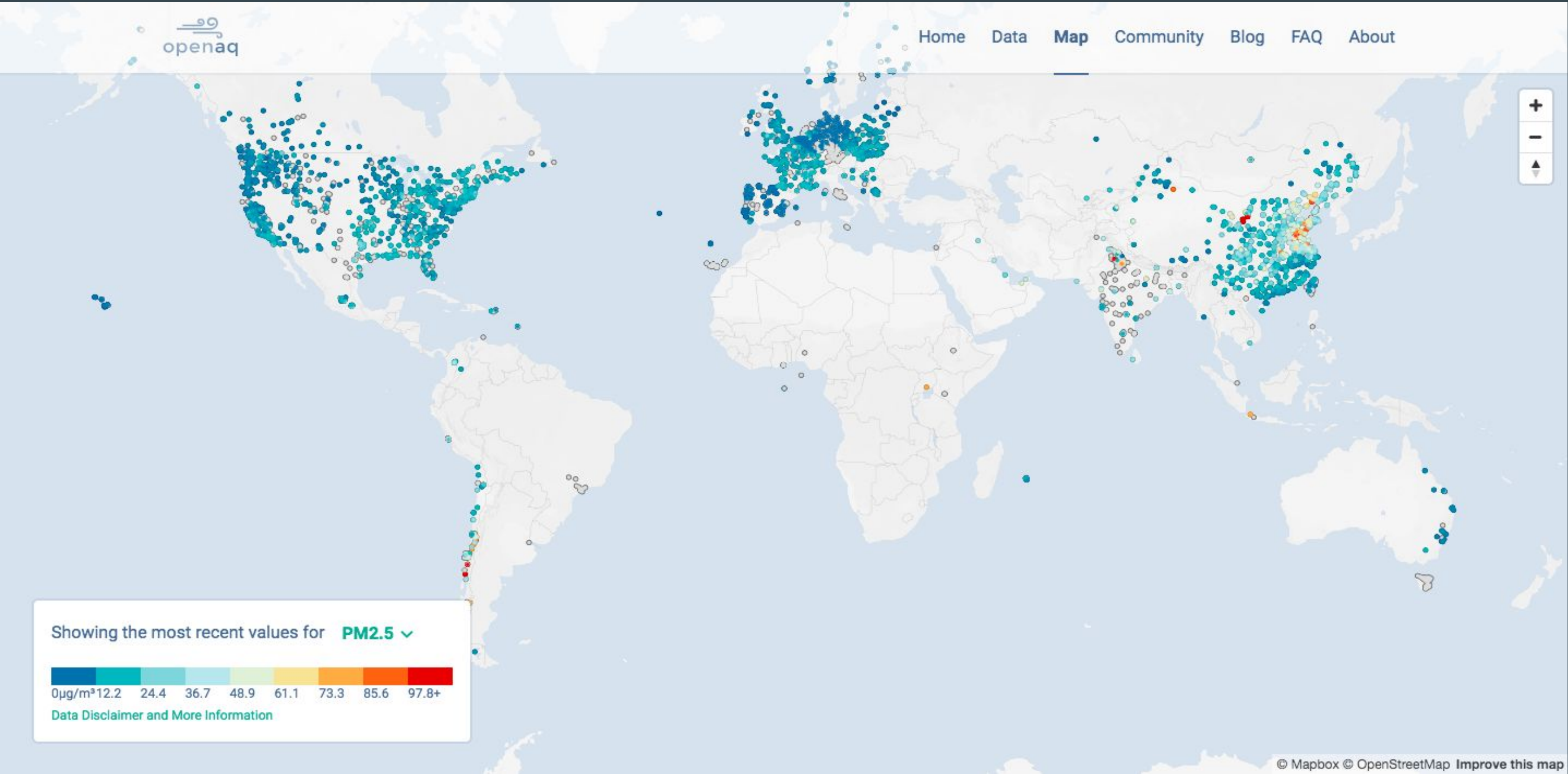

Background: air quality (AQ) data reported by countries

HUGE GAPS!

Motivations

- Low-cost sensors (LCS) could fill information gaps between reference monitors → "democratize" AQ data
  - Cost per instrument: $250 vs. $10,000+
- Concerns about measurement error from LCS
- Persistent air inequality between socioeconomic and demographic groups
  - Discrepancy increasing as overall AQ improves in U.S. (Jbaily et al., 2022)
- deSouza & Kinney (2021): PurpleAir sensors (most common $PM_{2.5}$ LCS) tend to be in more privileged areas

Motivations

Fine particulate matter ($PM_{2.5}$) is the air pollutant of most concern for human health

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- IRA and ARP → $$$ for enhanced community AQ monitoring
  - Priority: environmental justice (EJ) communities

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Local policy questions (examples):

1. Where should we place low-cost sensors to fill gaps in reference monitoring, to optimize both accuracy and equity of AQ reporting?
2. Given a budget for community AQ monitoring, what kind of improvement in reporting can we expect to see from deploying N sensors that have accuracy X?

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Considine et al. (2023) *Environmental Science & Technology*

Research questions:

1. How does the distribution (density and placement) of low-cost sensors affect real-time air quality (AQ) information, in terms of both accuracy and equity?
2. What mechanisms drive inaccurate AQ reporting?

Mechanisms driving errors in reported AQ

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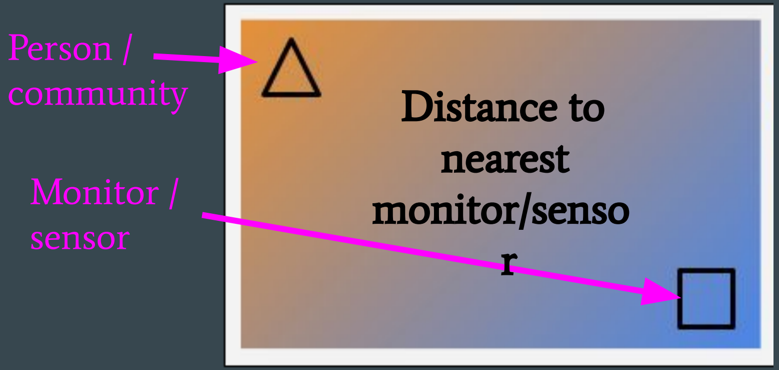

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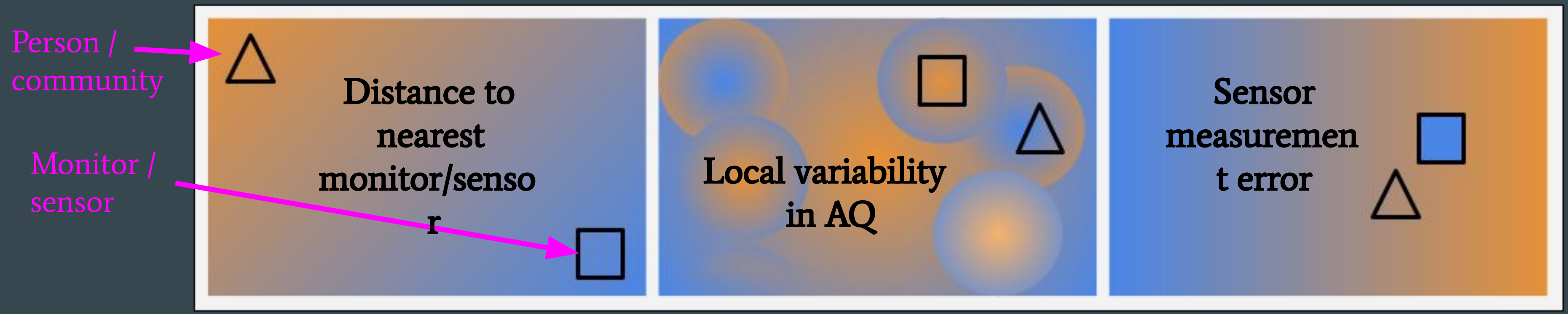

How do these mechanisms, individually and jointly, affect real-time AQ reporting?

→ *Compare counterfactual scenarios using simulations!*

Summary of approach

- Conduct a simulation study based closely on real data
- Consider AQ information from individuals' nearest AQ instrument (sensor or reference monitor) – both concentration and EPA AQI classification

Summary of approach

Air Quality Index Levels of Health Concern	Numerical Value
Good	0-50
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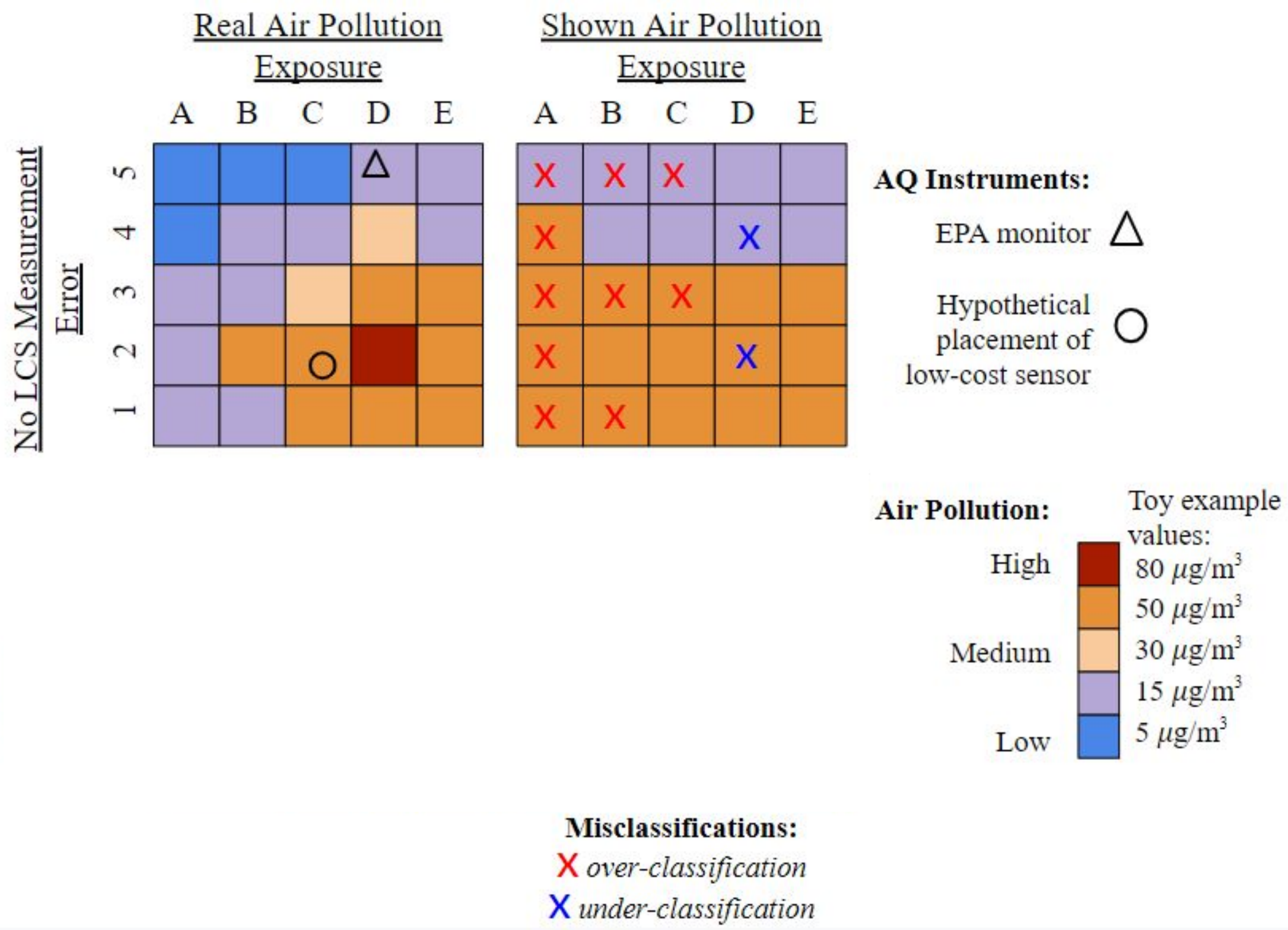
Real Air Pollution Exposure
Shown Air Pollution Exposure
A B C D E
No LCS Measurement Error
5
4
3
2
1
AQ Instruments:
EPA monitor
Hypothetical placement of low-cost sensor
Air Pollution:
Toy example values:
High
Medium
Low
80 μg/m3
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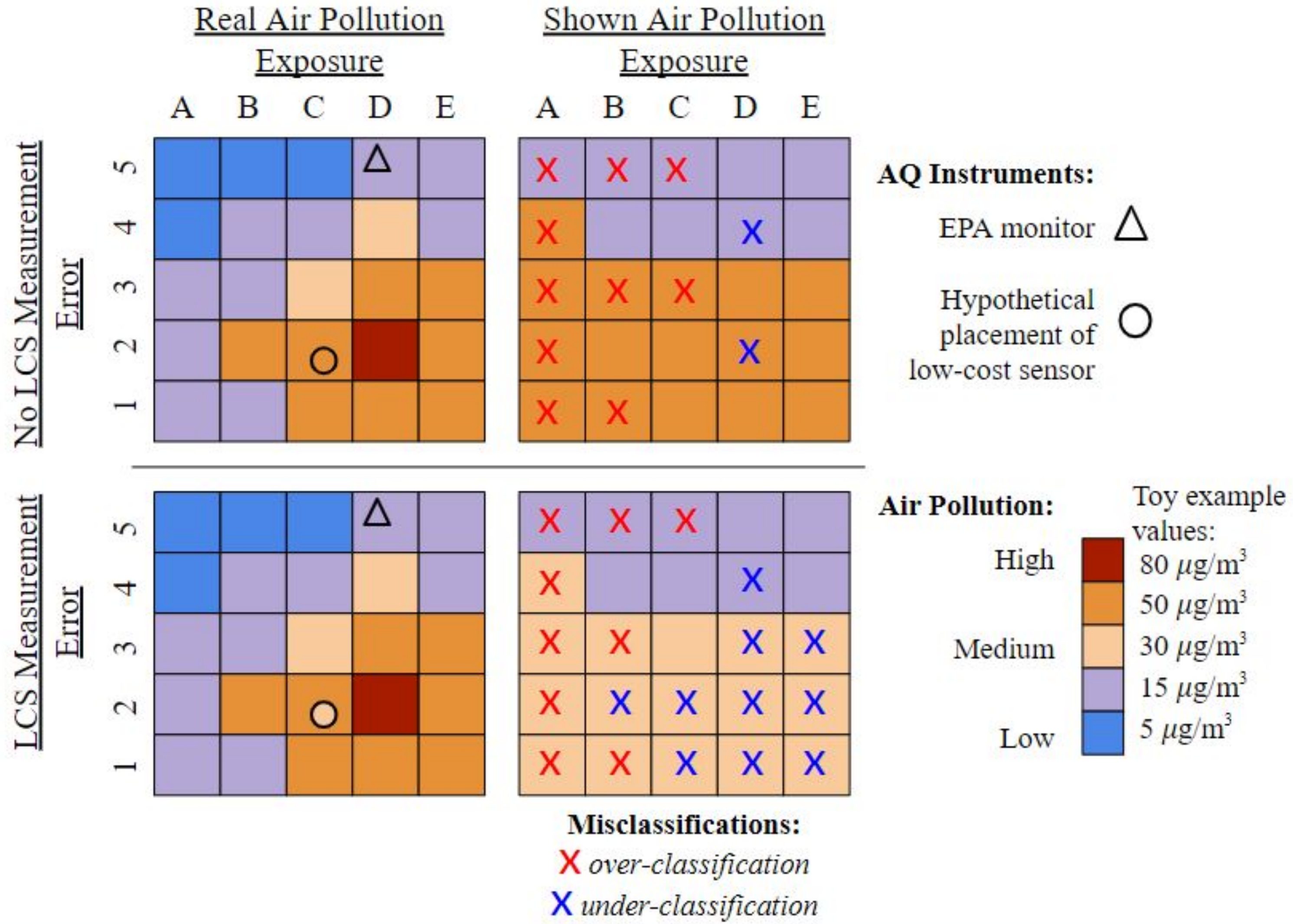
Misclassifications:
over-classification
under-classification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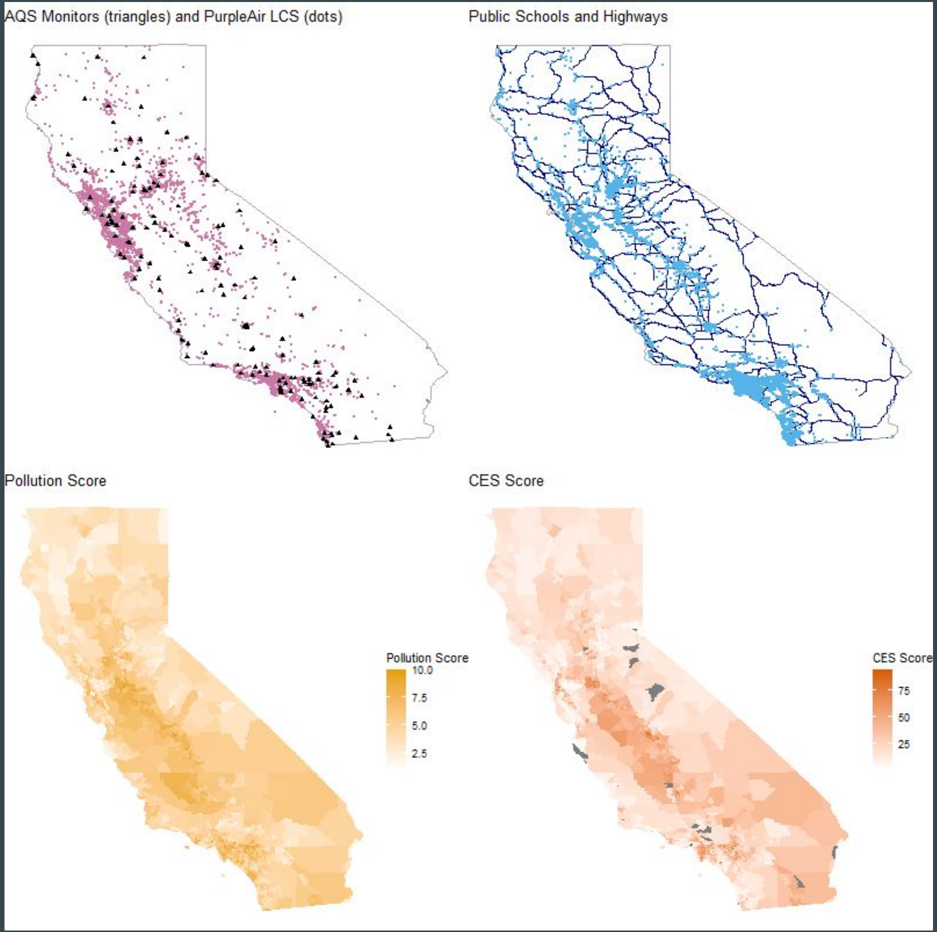
Placement strategies

Randomly-selected n = 50, 100, 250, 500, and 1,000:

- Current PurpleAir locations
- Schools
- Weighted by lengths of major roads within a 500m buffer
- Weighted by environmental and socioeconomic marginalization:
    - CalEnviroScreen: Pollution Score and compound CES Score



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- Characterize relationships between number of sensors, noisiness of sensor measurements, and prioritization of areas with environmental justice concerns

Simulation methodology

- Consider daily 1x1km Di et al. $PM_{2.5}$ estimates (machine learning-derived) “truth”
- Assume reference monitors have fixed locations and no measurement error
- Select LCS locations (based on one placement strategy), x 100 trials
- Simulate measurement error at “sensor” locations
- Each grid cell “sees” AQ info from the nearest monitor/sensor
- Calculate performance metrics (comparing the “true” AQ to the “shown” AQ), overall and by subgroups, averaged across the 100 trials
  - Weight by population density

Repeat for different types and amounts of sensor measurement error.

LCS measurement error simulation

- Build off well-known references:
  - EPA workshop on LCS accuracy standards: Williams, et al. (2019)
  - Linear correction for PurpleAir in U.S. developed by EPA researchers: Barkjohn, et al. (2021)
- Our simulations:
  - No LCS measurement error
  - Measurement error, 10% and 25% of “truth”
    - Non-differential
    - Differential
  - Sampled empirical residuals from EPA correction
    - Obtained from collocated monitor-PurpleAir pairs

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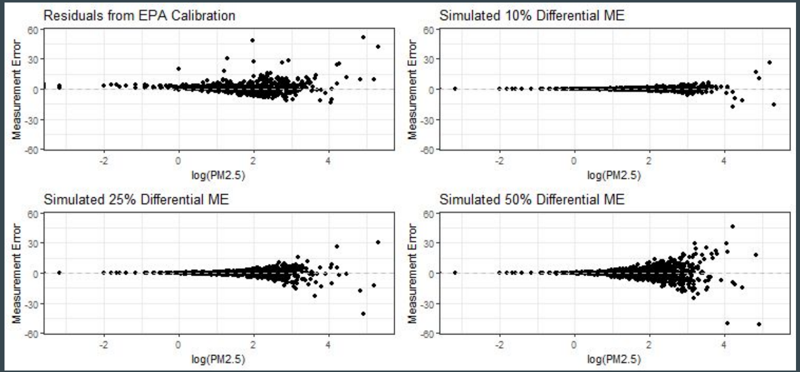
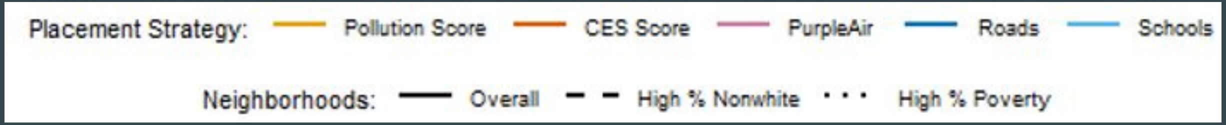
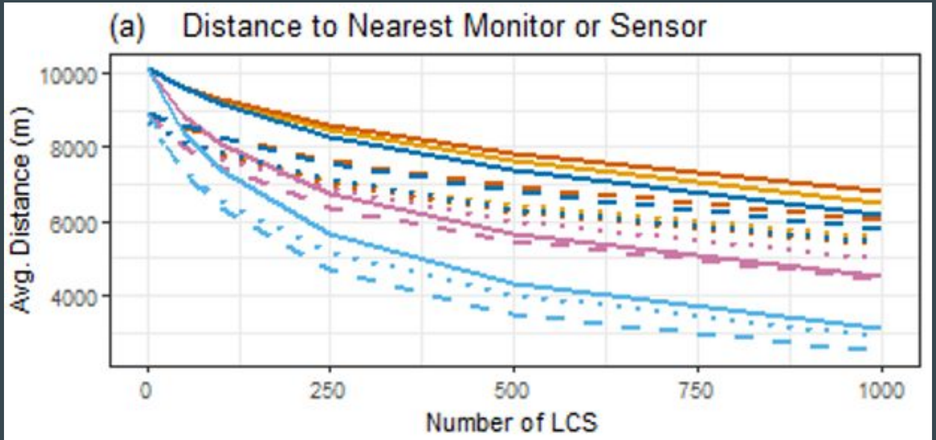


Now for some results...



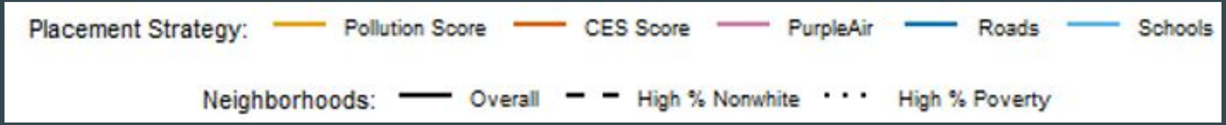
Census Block Groups (CBGs) in the top quintiles

Distance



With LCS at all PurpleAir locations (n=4,343), the avg. distance drops...

- Population overall: 10.1 km → 2.4 km
- CBGs with high % nonwhite residents: 8.9 km → 2.5 km
- CBGs with high % poverty: 8.7 km → 2.8 km



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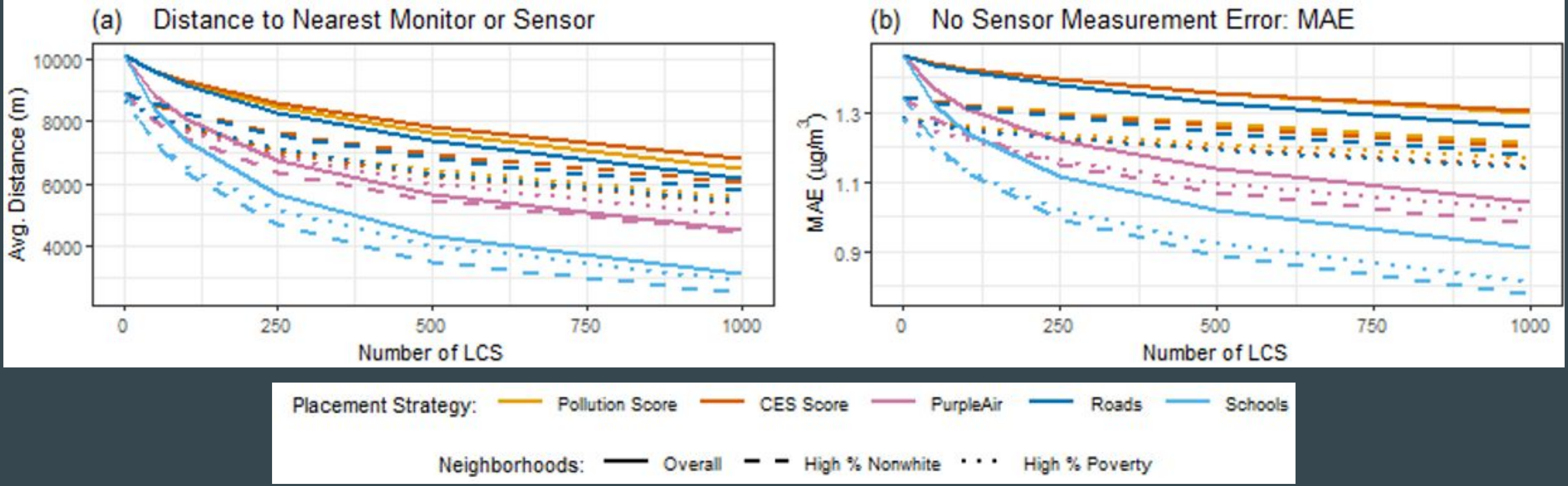
Distance and Mean Absolute Error (MAE) in AQ information



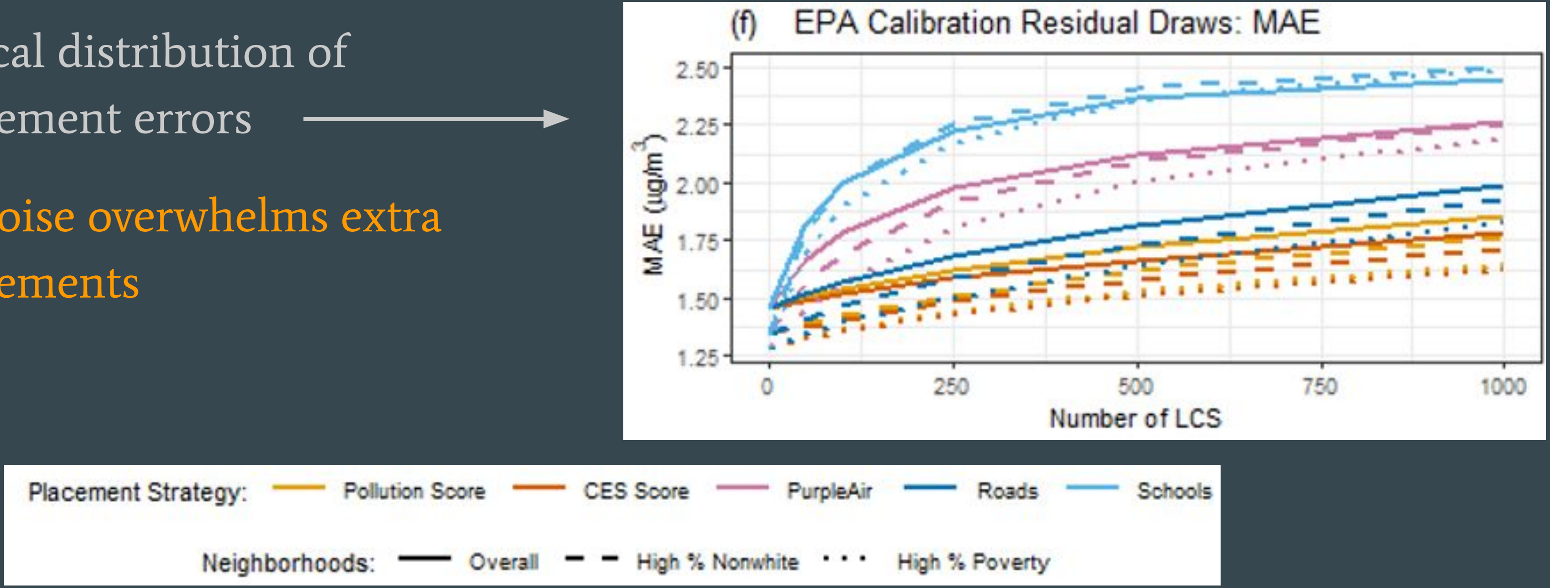
Very similar patterns!

Annual NAAQS for $PM_{2.5}$ is 9 $\mu g/m^3$

MAE with different amounts of sensor measurement error

Empirical distribution of measurement errors →

Extra noise overwhelms extra measurements



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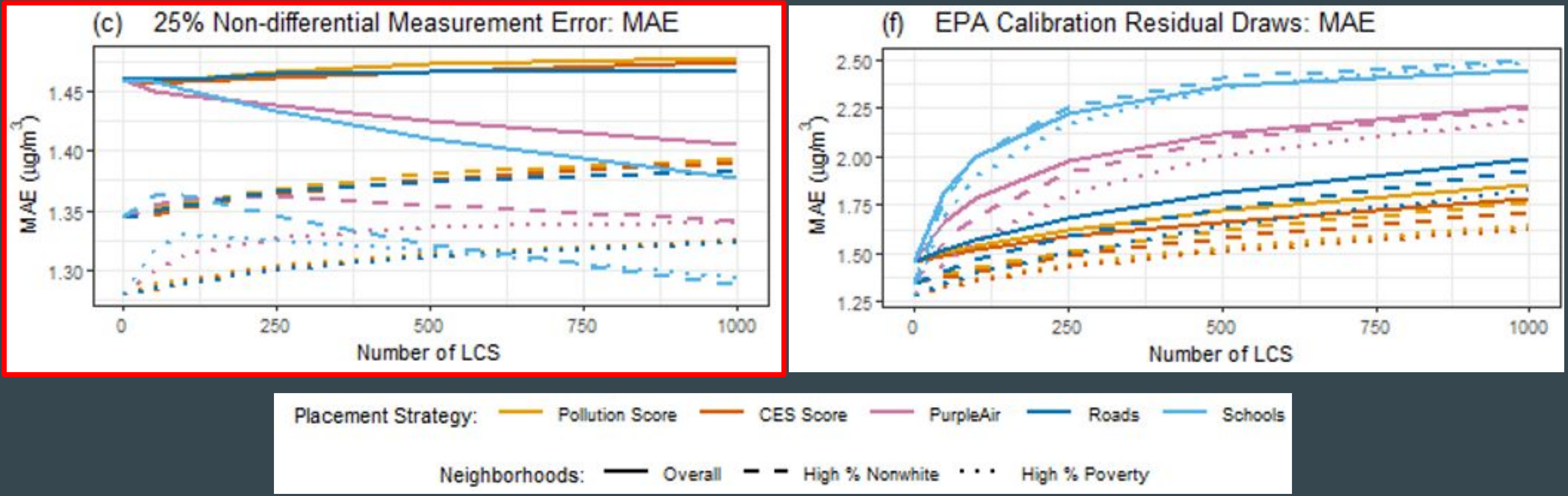

Turning point: some placement strategies improve accuracy, others worsen

Now consider misclassified observations

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Reported

True

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Large misclassifications (>1):

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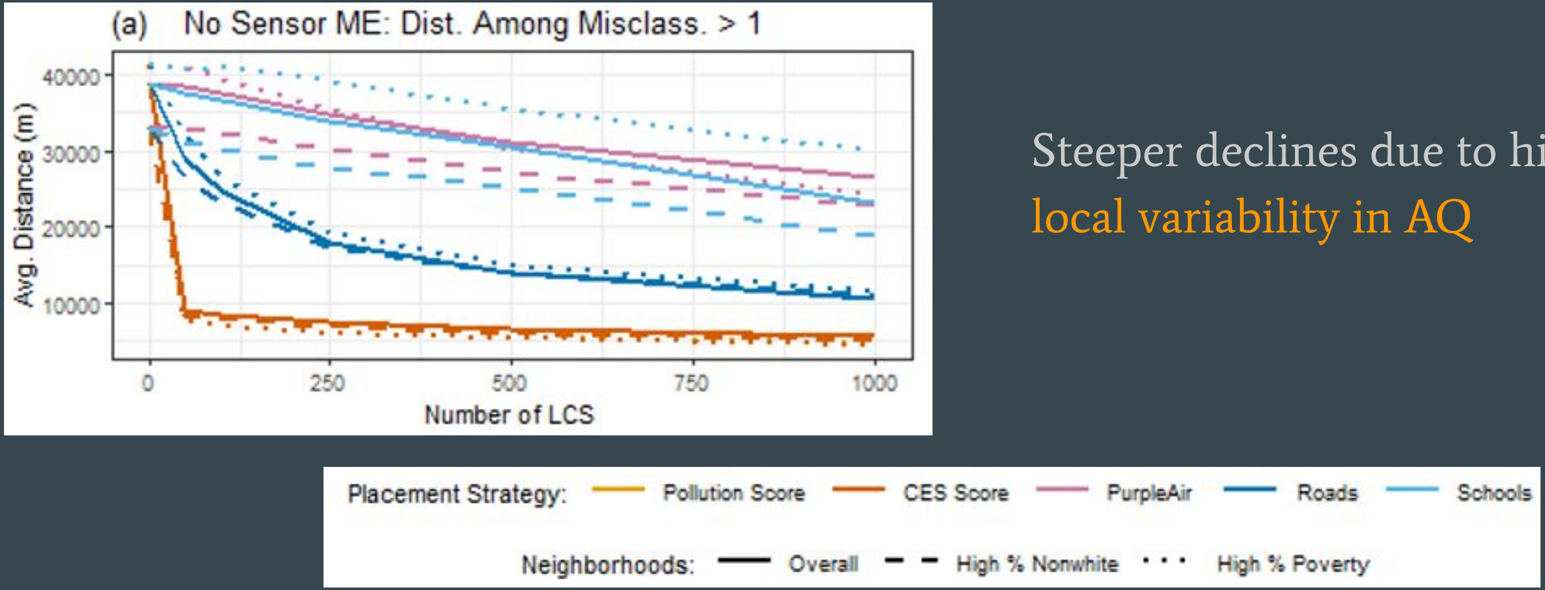
Distance to nearest AQ instrument, among large misclassifications



Steeper declines due to higher local variability in AQ

Doesn't discernibly change until we add lots of differential sensor measurement error...

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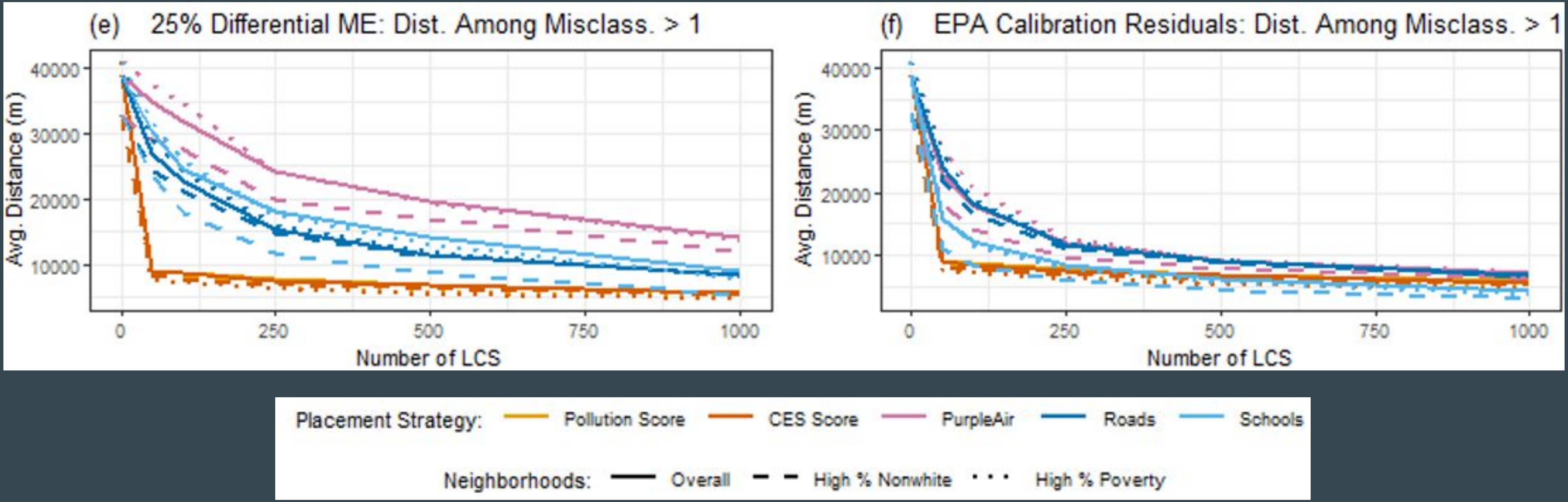

More and more observations being misclassified due to measurement error...

Differential measurement error makes large misclassifications more likely

Paper discusses more results related to AQI classifications...

Overall conclusions

- The value of using LCS for real-time AQ reporting depends strongly on type and amount of sensor measurement error (ME)
  - 25% non-differential ME appears to be workable for some placement strategies, but not others
  - LCS corrections may need to be more localized / advanced than a national linear correction
- With low-to-moderate amounts of ME (depends on type): placing LCS at schools results in the greatest improvement in AQ info, for all demographics considered, as the number of LCS increases – *also pragmatic (logistics + children's health)!*
- Placing LCS near pollution hotspots may help those in immediate vicinity, but can cause issues when integrated into wider AQ reporting platforms due to local variability
- Rural areas may need different strategies

Contributions

- Novel and easily modifiable methodology
  - Not mathematically advanced, but utilizes statistical / decision science analytical frameworks, emphasizes policy relevance
- Quantified impacts of LCS network characteristics on both accuracy and equity of real-time AQ reporting
  - Increased understanding of mechanism interactions
- Made recommendations both for LCS placement (at schools) and LCS measurement accuracy requirements