Detecting Plumes in Mobile Monitoring Time Series with Density-based Spatial Clustering of Applications with Noise

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Section S1. Description of temporal rescaling procedure.

Figures S1-S5

Tables S1-S3

**Section S1.** Rescaling procedure for census tract comparisons

To remove temporal effects from census tract comparisons, a rescaling procedure was implemented. The objective was to transform each census tract’s sampling distribution into a uniform distribution, then multiply each hour of the newly transformed uniform distribution by the fraction of detected anomalies in that hour.

Out of 35 census tracts in the Houston area, we constrict our analysis to 19 to ensure that each hour for every census tract between 8 AM and 3 PM, CST, had at least 1,000 samples. The lowest number of samples in any given hour for a census tract was 1,061, which equates to 17 minutes of sampling. For each census tract, we calculate the average number of samples per hour, determined by calculating the total number of samples and dividing by 8, which is the number of analyzed hours. In addition to calculating the average number of samples, we calculate for each hour in each census tract the fraction of that hour’s measurement that are of a given anomaly type (“CO2 – Rich”, “Transition”, “BC/UFP – Rich”). In the final step, we multiply the hourly fraction of each anomaly type by the average number of measurements for the census tract, and sum the results. To determine the % probability of detection for a given anomaly type, we divide these weighted totals by the number of measurements made within the census tract.

Figures S1 and S2 display the effects of implementing the rescaling procedure on the calculated probabilities of anomaly detection for the 19 census tracts. In general, we note that implementing the rescaling procedure results in modest increases in these probabilities across the board. A notable exception is the North Rice polygon for CO2 anomaly detections. Figure S3 displays the (a) total sampling distribution and (b) anomaly sampling distribution for the North Rice polygon. We note that the 8 AM hour was oversampled relative to other hours sampled and argue that implementing the rescaling procedure decreases the effects of this hour relative to other sampling times in the census tract.

Chart, bar chart

Description automatically generated

**Figure S1.** Effects of scaling on the probability of CO2 anomaly type detection for each census tract.

Chart, bar chart

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**Figure S2.** Effects of rescaling on probability of BC/UFP anomaly type detection for each census tract.

Chart

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**Figure S3.** Sampling distributions for (a) all measurements and (b) anomalies in the North Rice census tract.

Chart, bar chart

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**Figure S4.** Probability of detecting BC/UFP anomaly type with highways in the analysis (green) and without highways in the analysis (blue).

Chart, bar chart

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**Figure S5.** Probability of detecting CO2 anomaly type with and without highways.

**Table S1.** Instruments used in the Houston mobile monitoring campaign.

|  |  |
| --- | --- |
| Measured Pollutant | Instrument |
| Black Carbon (BC) (ng/m3) | AE33 (Aethalometer) |
| Carbon Dioxide (CO2) (ppm) | LI-7000 CO2/H2O Analyzer (Spectroscopy) |
| Nitric Oxide (NO) (ppb) | Teledyne T200 (Chemiluminescence) |
| Nitrogen Dioxide (NO2) (ppb) | Teledyne T500U (CAPS) |
| Ultrafine Particle Counts (UFP) (p/cm3) | Aerosol Dynamics MAGIC 200p (CPC) |

**Table S2.** Cross validation results for 5 folds.

|  |  |  |
| --- | --- | --- |
| Fold | Trained | Testing Performance (%) |
| 1 | 0.01 | 85.05 |
| 2 | 0.03 | 85.93 |
| 3 | 0.03 | 87.39 |
| 4 | 0.03 | 84.09 |
| 5 | 0.03 | 88.57 |

**Table S3.** Counts of when QOR or DBSCAN outperform the other under different circumstances.

|  |  |  |  |
| --- | --- | --- | --- |
| QOR Label | DBSCAN Label | Correct Label | Counts |
| “Anomaly” | “Normal” | “Normal” | 19456 |
| “Normal” | “Anomaly” | “Normal” | 6739 |
| “Normal” | “Anomaly” | “Anomaly” | 8183 |
| “Anomaly” | “Normal” | “Anomaly” | 12174 |