4 elementary schools trialing rover

22% >PM2.5 reduction at trial schools

Cost-effective, mobile AI-rover system engineered to evaluate impacts of microclimatic interactions on pediatric asthma

2.4K+ students impacted

2 prospective policies

1. Background

1.1: The problem — gaps in literature

The **effects of specific microclimatic parameters on pediatric asthma vulnerability (PAV)** and how varying levels of **vegetation influence pollutant exposure in urban school** environments are poorly understood at the **census tract level.**

Insufficient analysis of single pollutants
Many studies have **aggregated** pollutant data (e.g., into particulate matter (PM) and VOCs), which **obscures** the distinct **effects of individual pollutants** or pollutant sizes on PAV.
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Inconclusive microclimatic interactions
Existing research lacks analysis of how specific **meteorological factors** (e.g., temperature, humidity, wind speed) influence the **dispersion** / **concentration** of **pollutants** and **PAV** in urban school environments where **vegetation** varies.
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Knowledge necessary to address limitations of current air quality monitoring solutions

1.2: The problem — gaps in methodology

Stationary air quality monitoring
Current **sensors** are **expensive** and inefficient because they are stationary (rely on pollutants reaching fixed collection points), rather than removing PM in areas of **highest concentration.**
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Pollutant dispersion
Traditional sensors overlook how pollutants are diffused via **meteorological factors**—wind velocity, pressure, temperature variations (e.g., urban heat islands, thermal inversions).
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1.3: Purpose

- **Goal:** The goal of this study is to **clarify to what extent fine (>PM0.3) and coarse (>PM2.5) PM and carbon oxides (CO and CO_2) correlate with pediatric asthma vulnerability (PAV) in urban schools with low (<0.2) vs. moderate [0.2-0.6] NDVI (vegetation) at the census tract level.**
- **Methodology:** By testing a **cost-effective, mobile AI rover equipped with Arduino-based aerial sensors** for each microclimatic parameter.

1.4: Experimental design

- **Hypothesis:** We hypothesized that **schools in census tracts with less vegetation (lower NDVI)** would experience a **higher PAVI** compared to those in more vegetated tracts **due to increased exposure to microclimatic parameters**—particulate matter (PM), carbon monoxide (CO), and carbon dioxide (CO_2).
- **Independent variables:** Particulate matter, carbon oxides, greenness

>PM0.3 | >PM2.5 | CO | CO_2 | NDVI

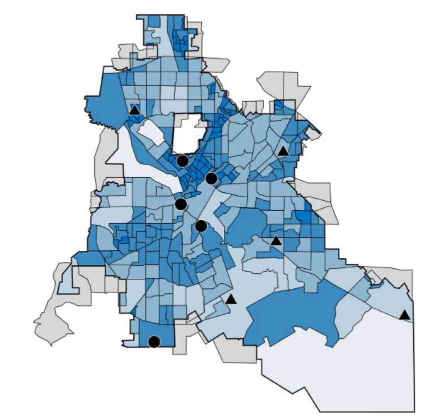
- **Dependent variable:** The PAV Index (PAVI) is defined by a high rate of ED visits and high COPD frequency coupled with low inhaler prescriptions.

$$\text{Macroscale PAVI} = \alpha(\text{ED visits}) + \beta(\text{COPD}) - \gamma(\text{Inhaler prescription})$$

- **Experimental group:** Schools with *low* NDVI
- **Control group:** Schools with *moderate* NDVI

2. Methodology

2.1: Site selection



Map created by finalist using Google Earth Engine® and Figma®, 2025

Average NDVI (greenness) values for census tracts in Dallas ISD

-1.0 to 0.0	0.0 to 0.2	0.2 to 0.4	0.4 to 0.6	0.6 to 1.0
Experimental schools	Experimental schools	Control schools	Control schools	

● Experimental schools (5) ▲ Control schools (5)

Experimental inclusion criteria: Dallas ISD public schools in census tracts of NDVI <0.2 and ≥5 years of PAV data, enrolling ≥500 students, and spaced >3 miles apart.

2.2: Data collection

- We gathered data on the selected atmospheric parameters at 10 selected Dallas ISD schools, divided into **5 experimental and 5 control locations**; for each, at 3 designated sublocations, with 3 replicates per sublocation, on 2 dates, totaling 180 trials. Sensors self-assembled from Arduino-based parts.
- Since there wasn't an affordable way to microsense wind speed, we engineered a proximity sensor + pinwheel to count rotations / time.

Final rover with sensors

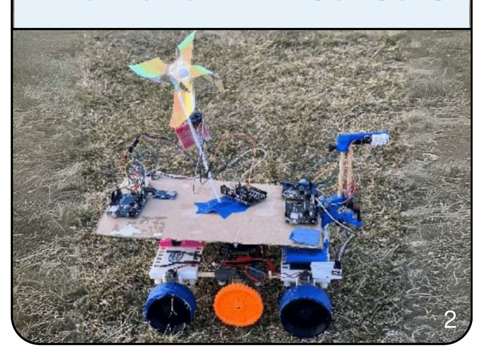


Photo taken by finalist, 2025.

Rover in schoolyard

Photo taken by finalist, 2025.

Rover chassis

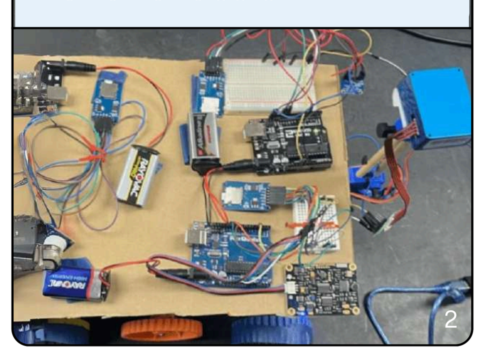
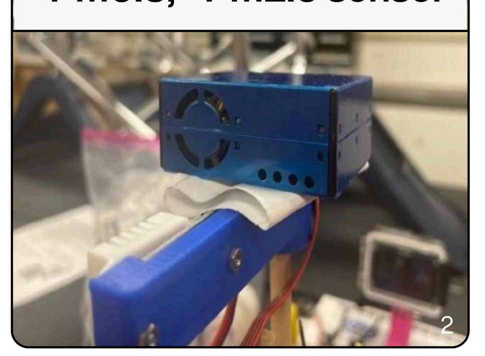


Photo taken by finalist, 2025.

>PM0.3, >PM2.5 sensor



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CAD 3D-printed wheels

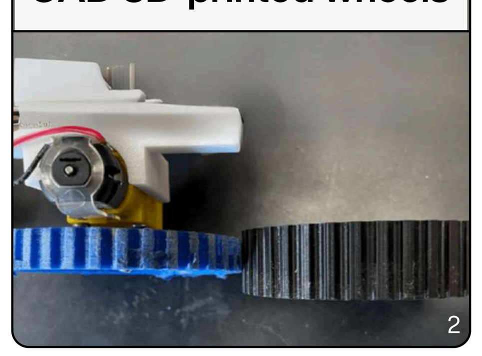
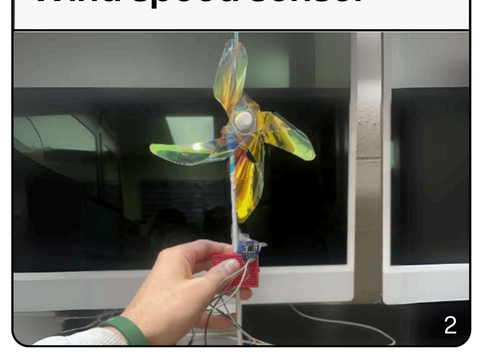


Photo taken by finalist, 2025.

Wind speed sensor



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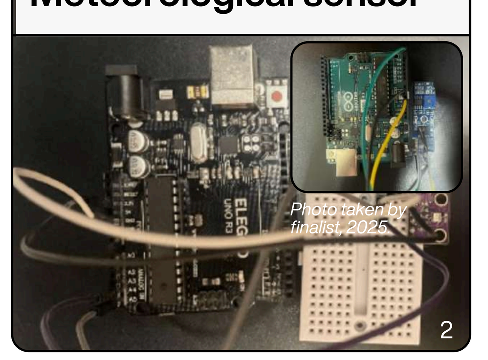
Meteorological sensor



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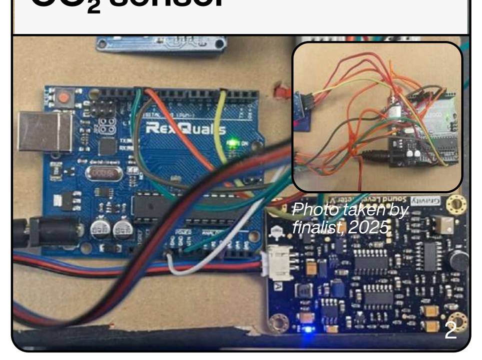
CO_2 sensor



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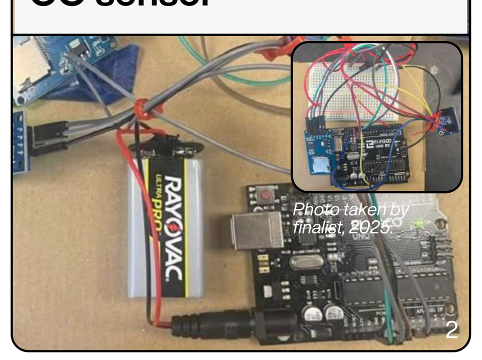
CO sensor



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2.3: Data pipeline + machine learning algorithm

1. **Transport rover** to each school; each with 3 sublocations; 3 replicates, 10 sec for 3 min/trial.
2. Rover either autonomously or remotely follows a standardized path; **transmits sensor data** to app.

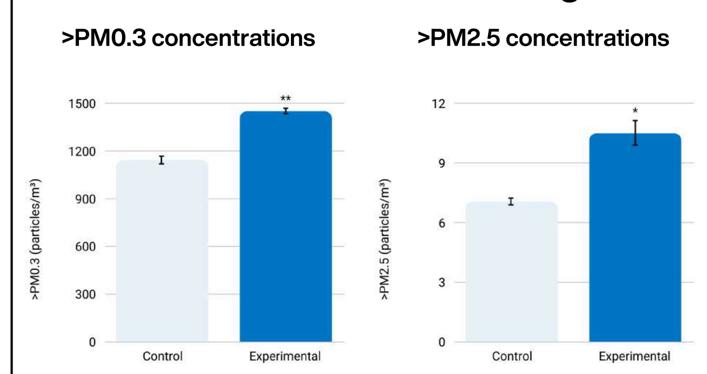
x3

- Each data point is linked with specific **coordinates** where the rover is located.
- Calculate **spatial covariance** between data points to assess how pollutant concentrations vary with distance.
- Apply the **Kriging model**, which uses the covariance matrix to predict pollutant concentrations at unmeasured locations.
- Use **DBSCAN clustering** to identify pollutant hotspots by grouping proximal areas with high pollutant concentrations.
- Pollutant dispersion model (with Gaussian dispersion) takes into account the movement of pollutants over time based on **meteorological** parameters.

3. Results

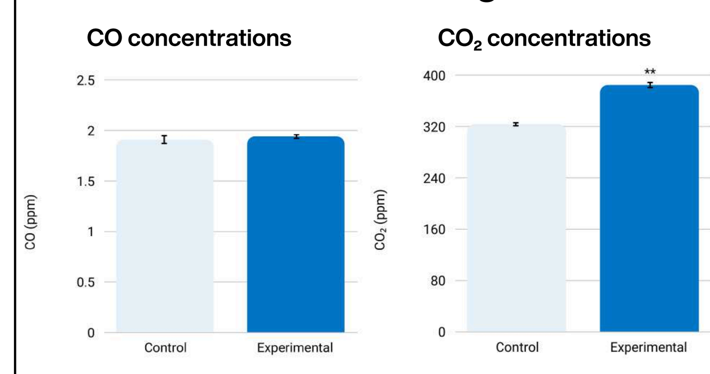
3.1: Microclimatic and meteorological parameters

Experimental schools record **27% higher >PM0.3** concentrations and **55% higher >PM2.5** concentrations than control schools on average[1]



Graph created by finalist using Canva®, 2025

Experimental schools record **2% higher CO** concentrations and **19% higher CO_2** concentrations than control schools on average[1]



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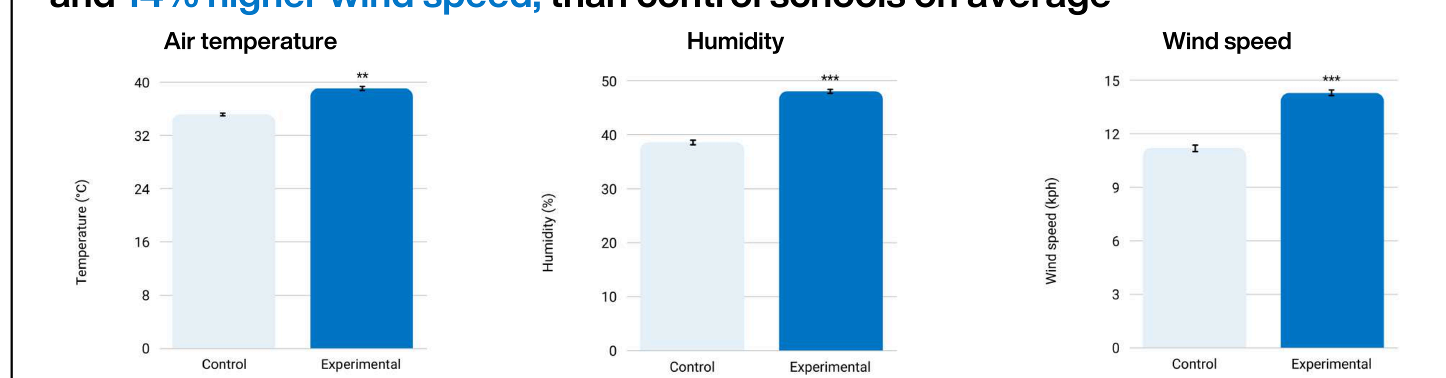
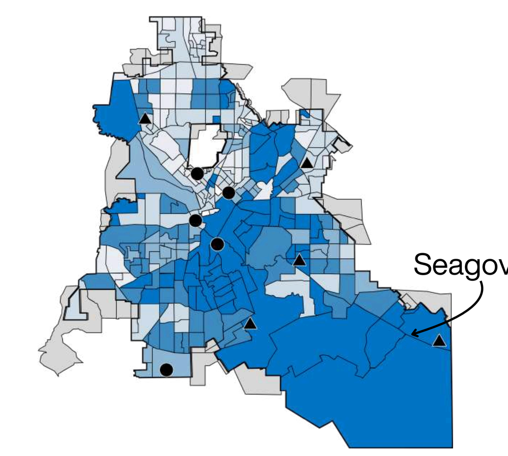
Experimental schools record **13% higher temperature**, **20% higher humidity**, and **14% higher wind speed**, than control schools on average[1]



Graph created by finalist using Canva®, 2025

3.2: Spatial trends in macroscale PAVI

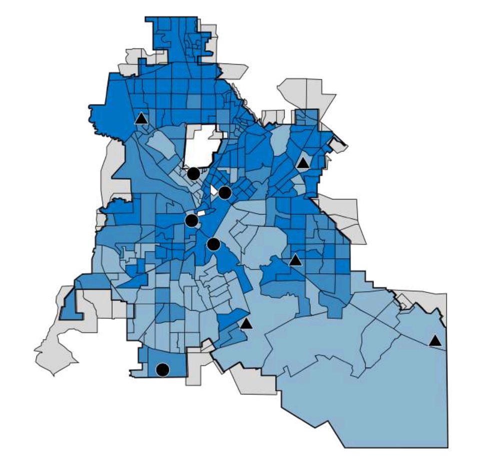
- **Experimental:** Spatial regression analysis revealed that **tracts in downtown Dallas showed a moderately high PAVI.** Those in the **urban periphery**, despite proximity to downtown, showed a **lower PAVI.**
- **Control:** Tracts in **Seagoville showed a high PAVI**, indicating over-reliance on preventive medication due to localized environmental triggers rather than health emergencies. North Dallas showed low PAVI, likely due to consistent healthcare access preventing acute asthma incidents in higher-risk areas.



ED visits caused by pediatric asthma/90 days

10-16	17-32	33-48	49-64	65-80

Map created by finalist using Google Earth Engine® and Figma®, 2025



Pediatric asthma patients prescribed inhaler/year

0-80	81-160	161-240	241-320	321-400+

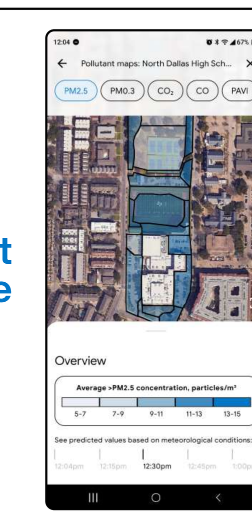
Map created by finalist using Google Earth Engine® and Figma®, 2025

Example: North Dallas High School (experimental school)

3. The model **builds a spatiotemporal map** of pollutant concentrations by visualizing pollutant dispersion relative to temperature, humidity, and wind speed to identify high-exposure zones.

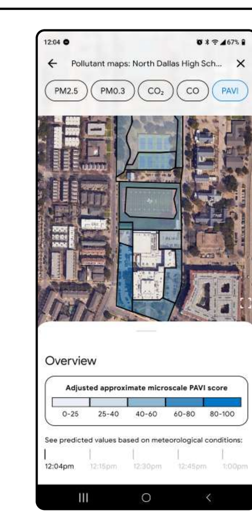
Screenshot taken by finalist, 2025.

Predict feature →



Screenshot taken by finalist, 2025.

Spatiotemporal >PM2.5 dispersion



Screenshot taken by finalist, 2025.

Trends, microscale PAVI:
- Highest in areas adjacent to major roads, parking lots, and building perimeters due to pollutant accumulation, reduced dispersion, and limited vegetation buffering.
- Lower PAVI observed in open fields and downwind locations where pollutants disperse more freely.

Microscale PAVI

4. Implications

4.1: Conclusions

- Experimental schools with **lower NDVI** experienced significantly **higher levels of CO_2 and PM (to a greater extent coarse PM), which were strongly correlated to increased PAV, especially in downtown and southeast Dallas.**
- **The inverse relationship between NDVI and temperature, CO_2, PM, and humidity** suggests that **low vegetation density directly contributes to worsened air quality and higher PAVI** in experimental schools.
- Experimental schools experienced significantly **higher microclimatic temperatures**, indicating a strong urban heat island effect caused by impervious surfaces replacing natural vegetation.
- Site-specific wind flow, temperature gradients, and vegetation density creates concentrated >PM2.5 exposure zones near traffic-adjacent school microclimates in low-NDVI areas.

4.2: Significance + impact on policy

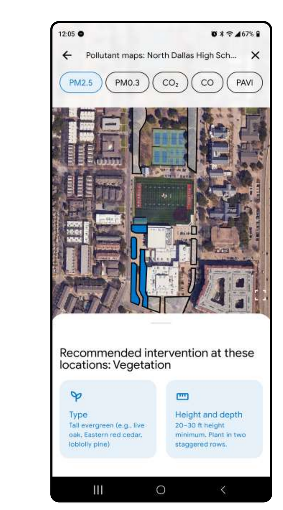
- This is the **first study** to assess the impact of microclimatic parameters on pediatric asthma prevalence and to integrate **machine learning to spatially visualize pollutant dispersion** while using **statistical analysis to compare differences between experimental and control groups.**
- The **rover-AI system's portability, affordability, and intelligence** make it a viable air quality monitoring tool for urban schools by informing **policy decisions tailored to their unique microclimatic conditions** rather than a reliance on **climatic data averaged across a ZIP code.**
- **This study's spatial insights are being used to lobby school officials to implement 2 atmospheric safety protocols in Dallas ISD elementary schools for the 25-26 school year.**
- Our rover overcomes the spatial/mobility limitations associated with traditional sensors. **Currently deployed in 4 Dallas ISD elementary schools totaling 2.4K+ students**, its affordability and portability make an ideal air quality monitoring tool.
- The rover-AI system led to an average of **22% reduction in >PM2.5 concentrations** at these **schools.**

4.3: Limitations + future work

- Social determinants of health, such as **higher poverty rates in experimental locations**, is a confounding variable that correlates with increased rates of chronic diseases and could have increased PAV independent of environmental exposures.

*1. p > 0.0001, *p ≤ 0.0001, and **p < 0.0001 represent significance values derived from unpaired two-sample t-test for the average values of each parameter in the experimental group compared to the control group.*
2. Data collection was conducted exclusively in public areas, adhering to posted signage at each site indicating publicly open hours and on non-operational days to comply with Dallas ISD policy.

4. The model generates **recommendations** on optimal intervention (e.g., vegetation, HVACs, HEPA) to reduce PAV.



Screenshot taken by finalist, 2025.

Interventions

Recommendation system:
- The app uses a hybrid Kriging interpolation + DBSCAN clustering model to generate spatiotemporal PM2.5 **dispersion maps** by using Gaussian pollutant transport simulations with analysis of meteorological covariance.
- Applies a **proximal policy optimization algorithm** to recommend vegetation and air filter placement, density, and species selection by identifying pollutant hotspots, dominant wind flow paths, and areas with high microscale PAVI.