AAM-LASSI (Ambient Air Monitoring of LPG At Scale in South India)

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BIRCHE^3 BERKELEY INTERDISCIPLINARY RESEARCH ON CLIMATE, HEALTH, AND ENERGY, EQUITY, ENVIRONMENT

Sri Ramachandra Institute of Higher Education and Research (SRIHER)

Center for Occupational and Environmental Health (COEH)

Clean Cooking Implementation Science Network (ISN)

STEER Environmental Health Science Internship Program

https://householdenergy.org/

Tamil Nadu, India

Outline

01. Background
02. Location
03. Objectives
04. Sensors
05. Data Analysis

Nagudi, Tamil Nadu, India

Background

Why India?

~ 26% of global deaths attributed to household air pollution are from India.

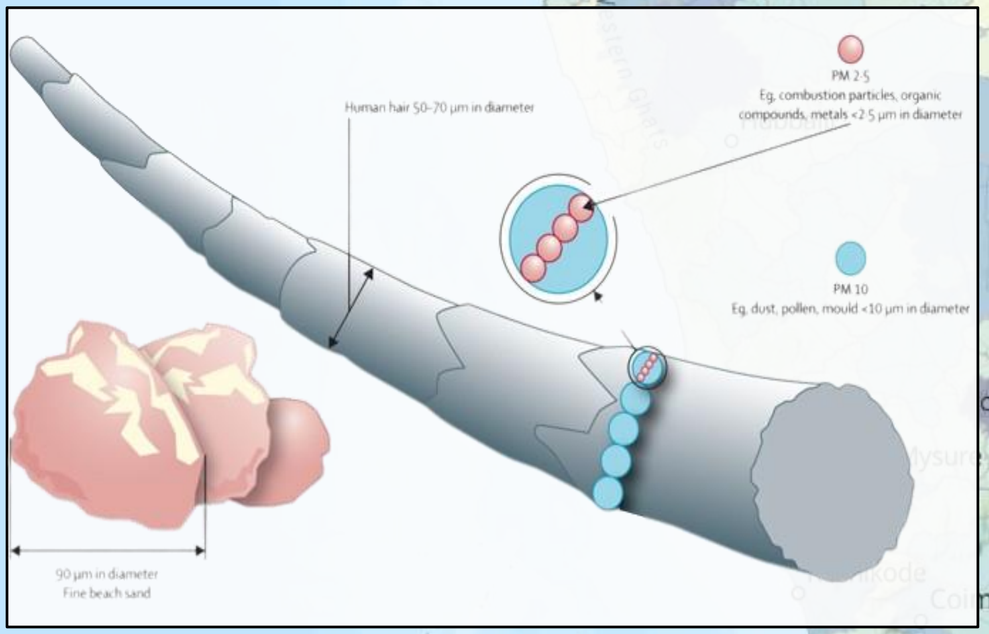
- Ambient and indoor air pollution cause **~1.7 million premature deaths** in India annually.[1]
- Both rural populations and the urban poor are the most susceptible and affected, but **rural areas have been understudied**.

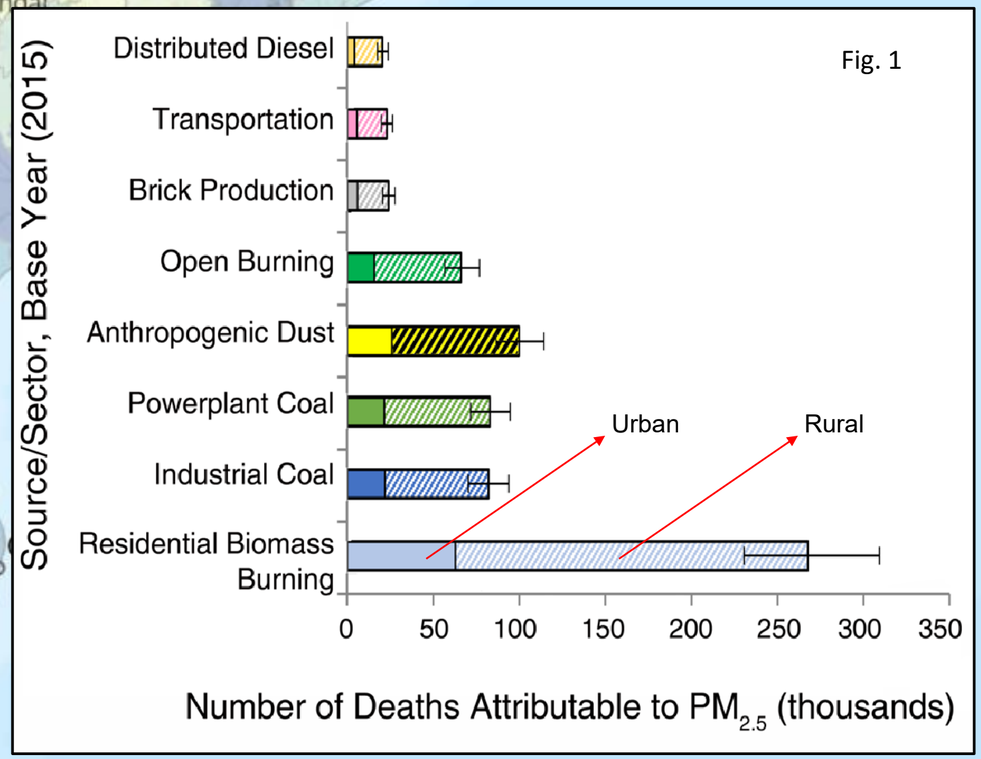
(1,2.) Traditional biomass cookstove
(3.) LPG cookstove

LPG: Liquefied petroleum gas

[1] *Indian Council of Medical Research, 2019.*

Background: $PM_{2.5}$





Contributions (95% CI) by selected sources to mortality burden in India in 2015.

What is $PM_{2.5}$ & where does it come from?

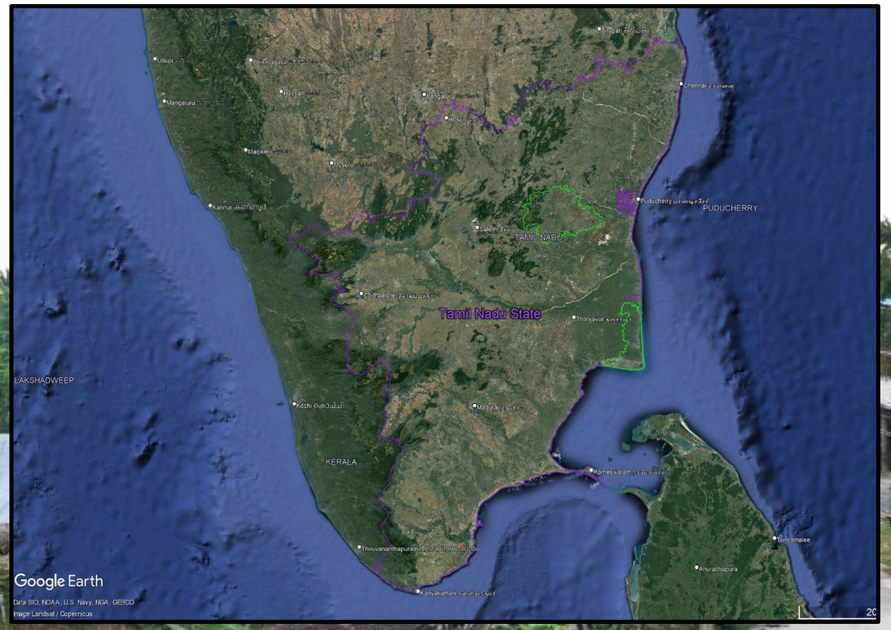
- $PM_{2.5}$ has a diameter of less than 2.5 µm, about one-thirtieth the width of a human hair.
- Common sources include emissions from burning fossil fuels such as coal or oil and biomass such as wood, charcoal, or crop residues.

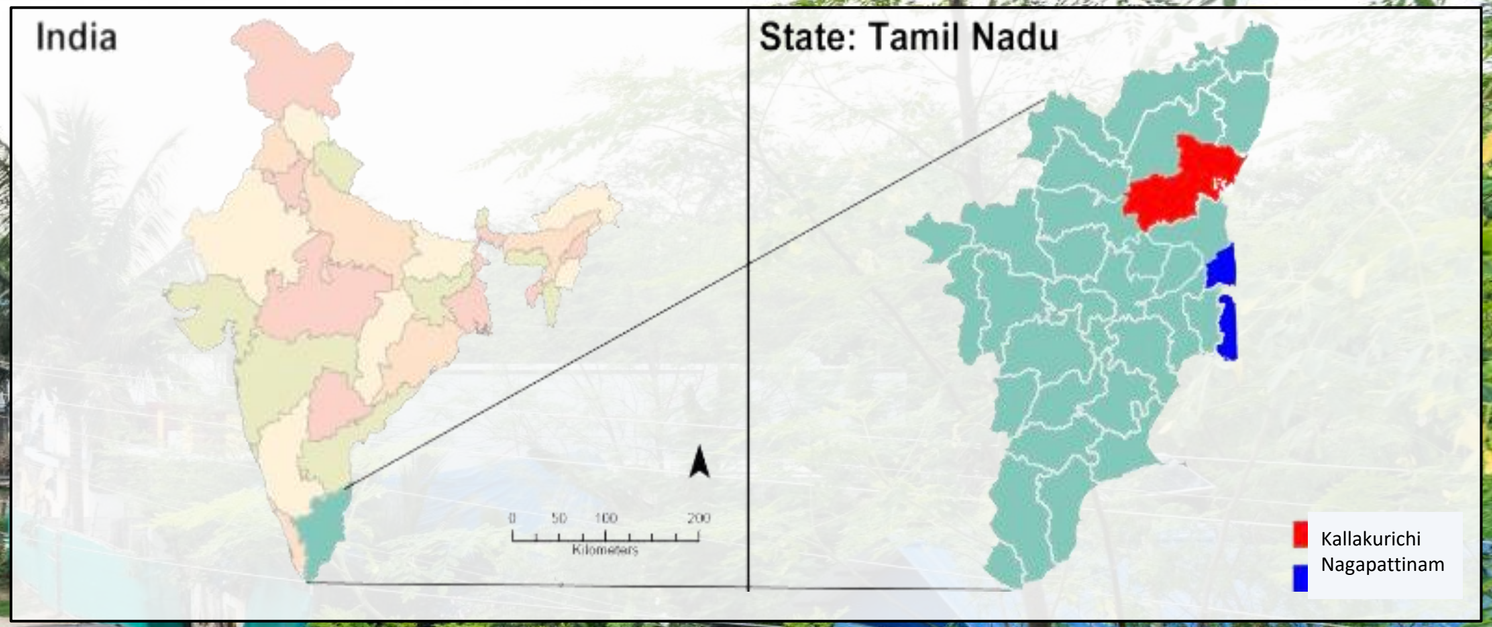
Impacts of $PM_{2.5}$

- $PM_{2.5}$ impacts a range of cardiovascular and respiratory diseases, including stroke, ischemic heart disease (IHD, chronic obstructive pulmonary disease (COPD), and lung cancer.

[2] *World Health Organization, 2021; Fig 1. GBD MAPS Working Group, HEI, 2018*

Location





- 16 rural villages selected from two districts of **Kallakurichi** and **Nagapattinam**
- ~**120 sensors** in 10 neighborhoods
- Study sites are far (> **100 km**) from major cities/towns and sources.

Poolangudi, Tamil Nadu, India


Kumbakonam கும்பகோணம்
Papanasam பாபநாசம்
Kuttanur குட்டனூர்
Karaikal காரைக்கால்
Nannilam நன்னிலம்
Tirumalairayan Pattinam திருமலைராயன் பட்டினம்
Poolangudi
Nangudi
Thanjavur தஞ்சாவூர்
Needamangalam நீடாமங்கலம்
Thiruvarur திருவாரூர்
Nagapattinam நாகப்பட்டினம்
Koothanallur கூத்தாநல்லூர்
Mayilangai
Keelakannapur
Velankanni வேளாங்கண்ணி
Mannargudi மன்னார்குடி
Orathanadu ஒரத்தநாடு
Nagapattinam District
Thruthuraipoondi திருத்துறைப்பூண்டி
Madukkur மடுக்கூர்
Karambakkudi கறம்பக்குடி
Pattukkottai பட்டுக்கோட்டை
Muthupet முத்துப்பேட்டை
Vedaranyam வேதாரண்யம்
Adirampattinam அதிராம்பட்டினம்
Kodiyakarai கோடியக்கரை
Google Earth
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image © 2022 Maxar Technologies
Image © 2022 TerraMetrics
Image © 2022 CNES / Airbus
N
20 km


Kallakurichi District
Moolakadu
Mottaiyanur
Mealvenniur
Kodamathi
Theerthamalai தீர்த்தமலை
Thanipadi தனிபாடி
Vettavalam வேட்டவலம்
Matur மத்தூர்
Pkoilom பகோயில்லோம்
Naripalli நரிப்பள்ளி
Akkarapatti அக்கரபட்டி
Kandachipuram கண்டாச்சிபுரம்
Vikravandi விக்கிரவாண்டி
Manalurpettai மணலூர்பேட்டை
Suramatham சுரமம்
Thirukoilure திருக்கோவிலூர்
Viluppuram விழுப்புரம்
Sankarapuram சங்கராபுரம்
Thiruvennainallur திருவெண்ணெய்நல்லூர்
Karumandurai கருமந்துறை
Rishivandiyam ரிஷிவந்தியம்
Tumbal தும்பல்
Vadakkanandal வடக்கனந்தல்
Panruti பண்ருட்டி
Kallakkurichi கள்ளக்குறிச்சி
Kilpalium கிழ்பாலியும்
Sengurichi செங்குறிச்சி
Ulundurpet உளுந்தூர்பேட்டை
Chinnasalem சின்னசேலம்
Neyveli T.S நெய்வேலி T.S
Attur அத்தூர்
Thalaivasal தலைவாசல்
Kurinjipadi குறிஞ்சிப்பாடி
Neyveli நெய்வேலி
Veppur வேப்பூர்
Virudhachalam விருத்தாச்சலம்
Gangavalli கங்கவள்ளி
Google Earth
Image © 2022 Maxar Technologies
Image © 2022 CNES / Airbus
N
20 km

Project Objectives

✧ **Clean and visualize ambient $PM_{2.5}$ data** from Tamil Nadu habitations using R packages (dplyr, tidyverse, lubridate, etc.)

✧ Provide **summary statistics** of PM levels by location, month, and season.

✧ Recursive sampling analysis to determine a suitable number of datapoints.

Investigation:

- Examine sensor data quality.
- How do $PM_{2.5}$ levels fluctuate hourly when summarized?
- How much variability is between the two study districts?
- How much sampling is enough sampling?

Mavilangai, Tamil Nadu, India

Sensors & Data

LCS: Low Cost Sensor

LCS Atmos

LCS Aerogram

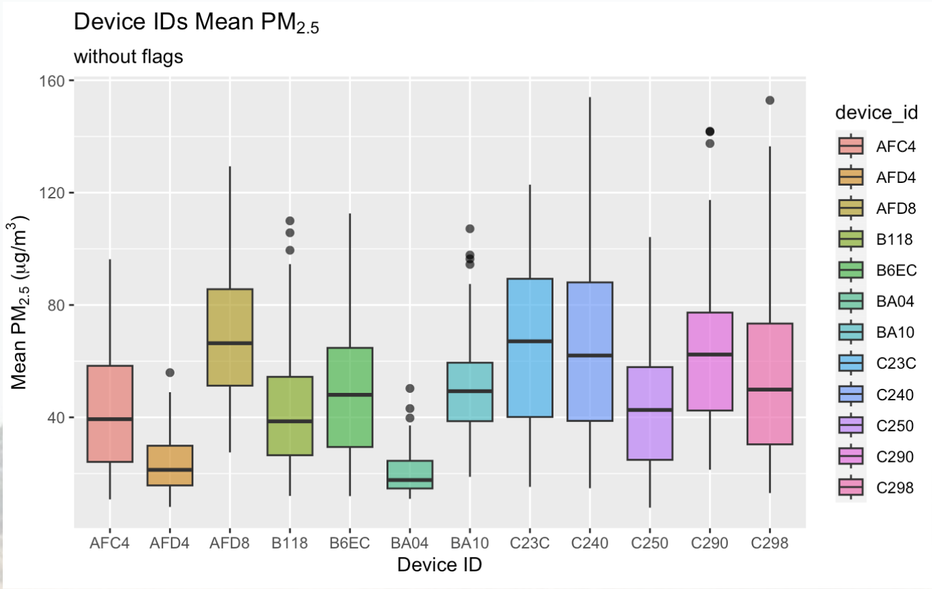
Original dataset from Atmos and Aerogram:
4,731,027 rows
- Data points taken up to every minute
- Data from Oct. 2021 to April 2023

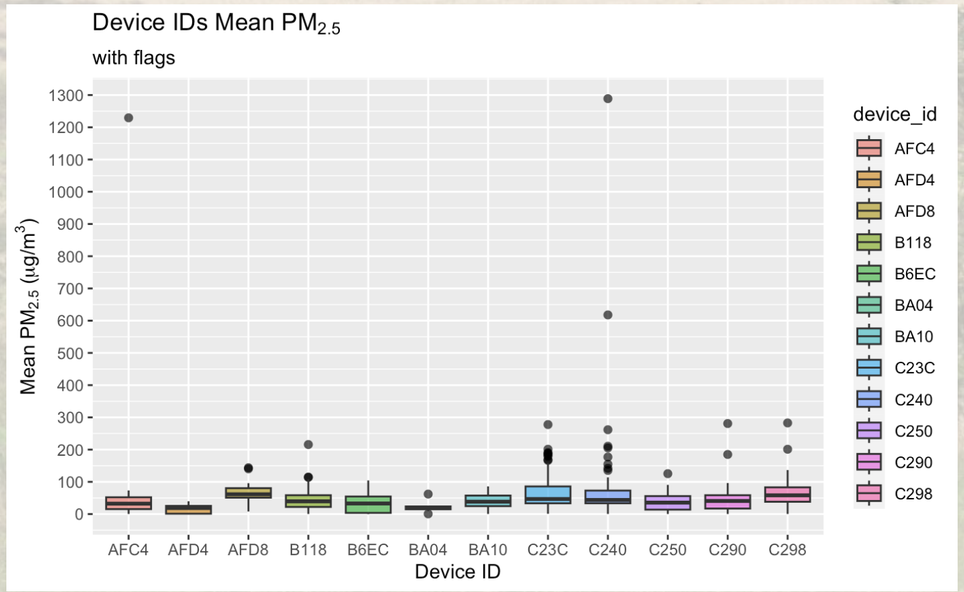
3,931,382 rows without colocation
3,368,468 rows without flagged

Dataset includes:
Device ID, district, latitude/longitude, timestamp, relative humidity, temperature, pm 1, 2.5, 10, and primary and secondary cookstove (traditional or LPG)

Mavilangai, Tamil Nadu, India

Data Cleaning and Merging





Data Flags:

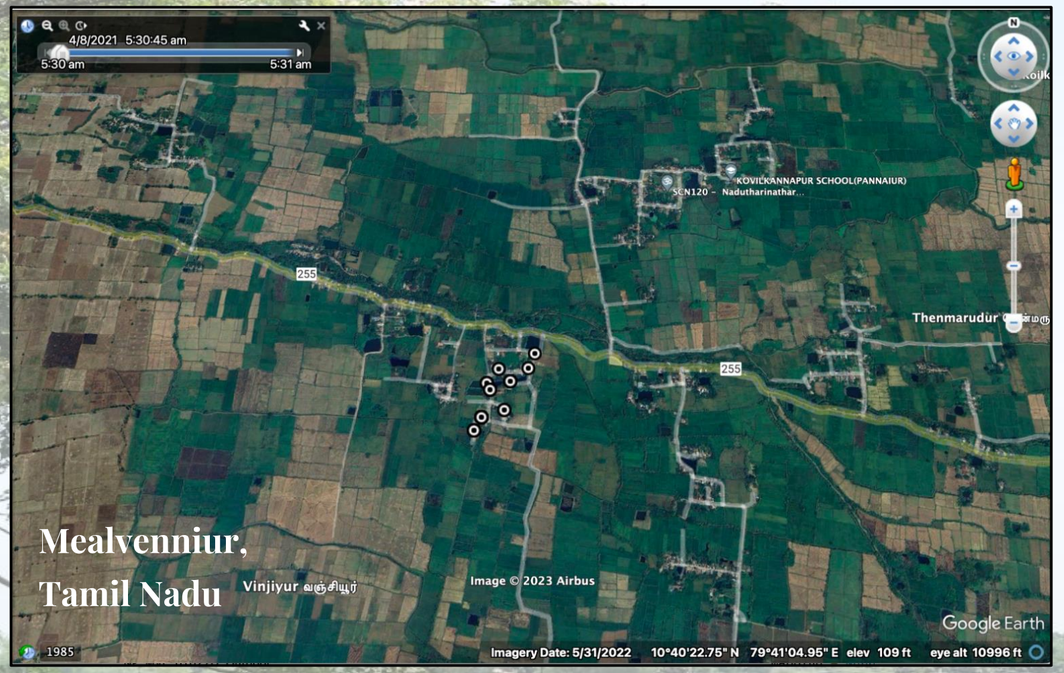
```
flagdict = {'temp': [10, 50], #(valid temp is >=10, <=50)
            'rh': [5,95],
            'pm1': [0, 2000], #(valid pm >0, <2000)
            'pm4': [0, 2000],
            'pm2.5': [0, 2000],
            'pm10': [0, 2000]
            }
```

562,914 points were flagged

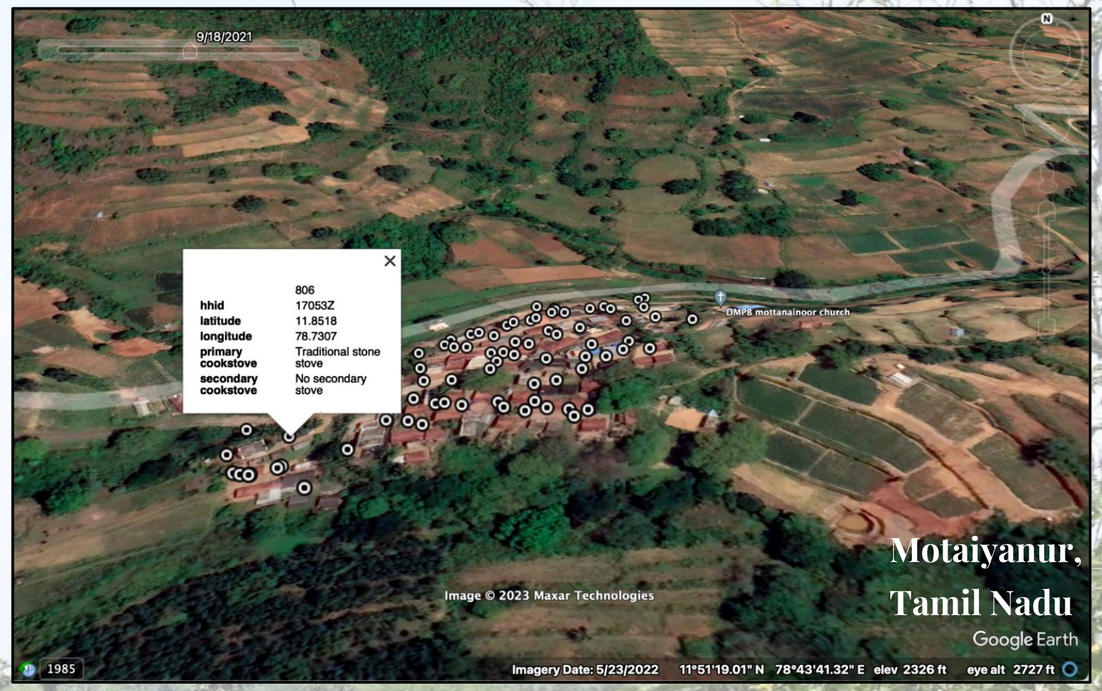
Merge:

- Merging device data with **metadata** for information about site, district, habitation, household ID, sensor type
- Then merged with **location data** for latitude, longitude, and primary and secondary cookstove information
  - Allowed for geospatial visualization

Sensor Geospatial Images

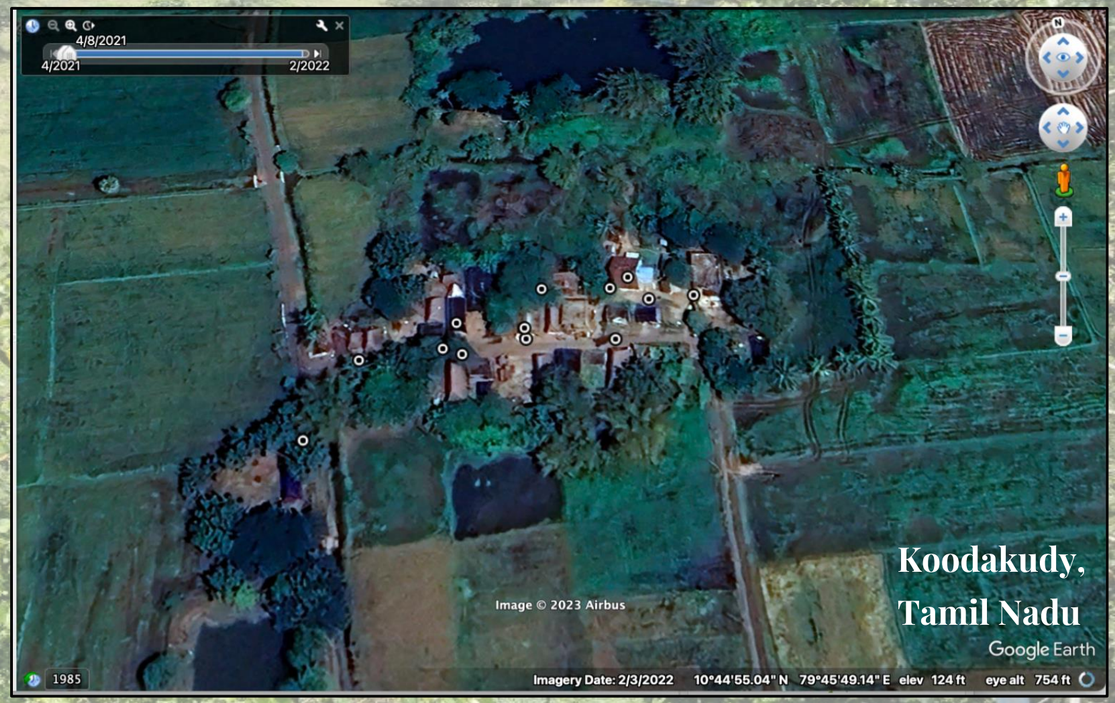


Mealvenniur,
Tamil Nadu



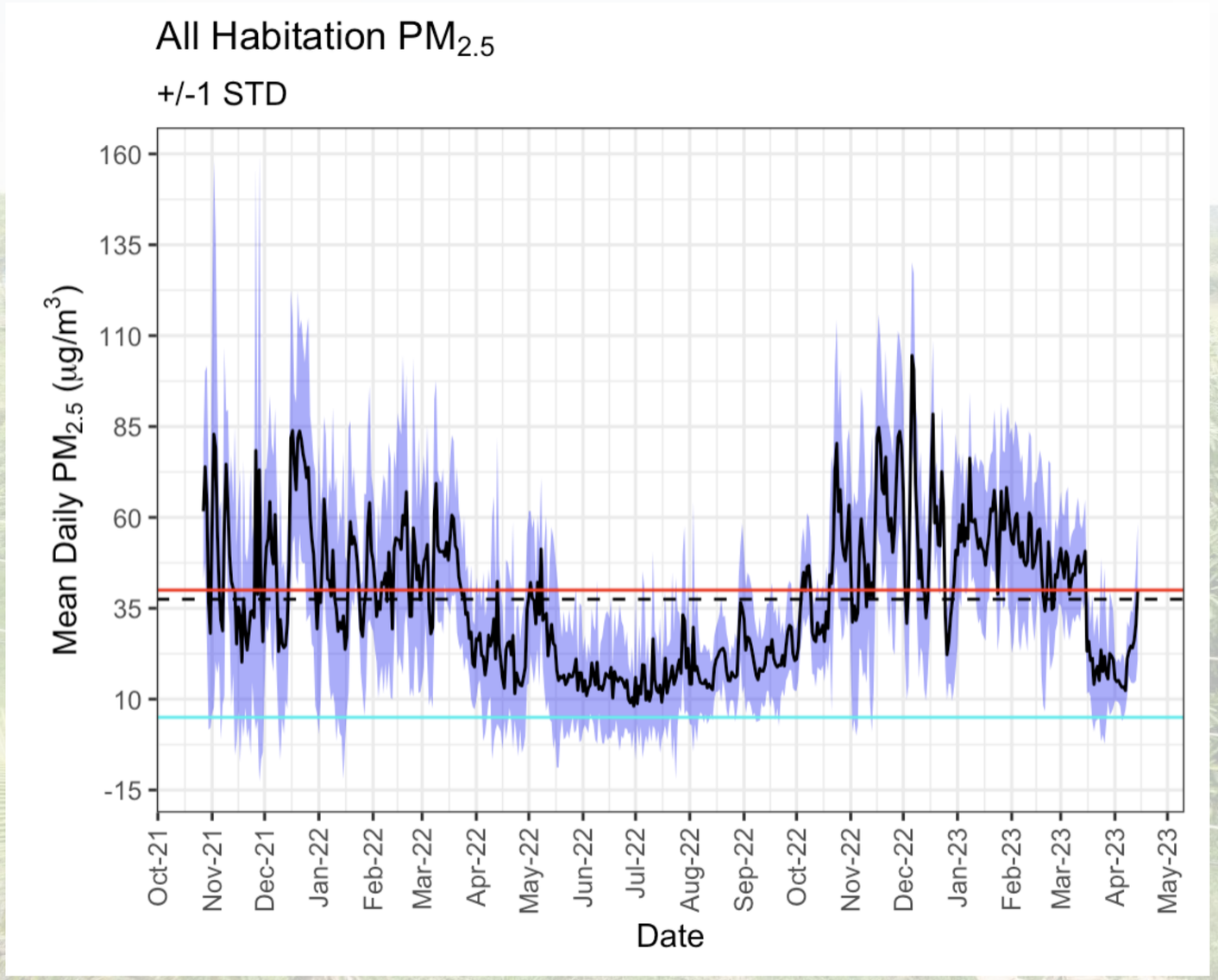
Motaiyanur,
Tamil Nadu

Mavilangai,
Tamil Nadu



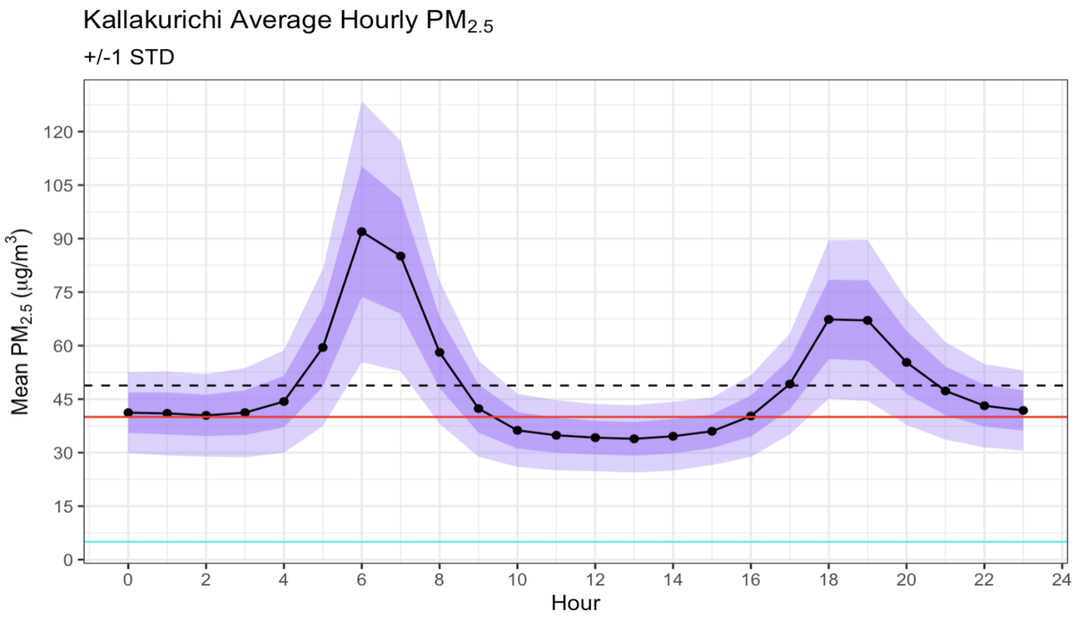
Koodakudy,
Tamil Nadu

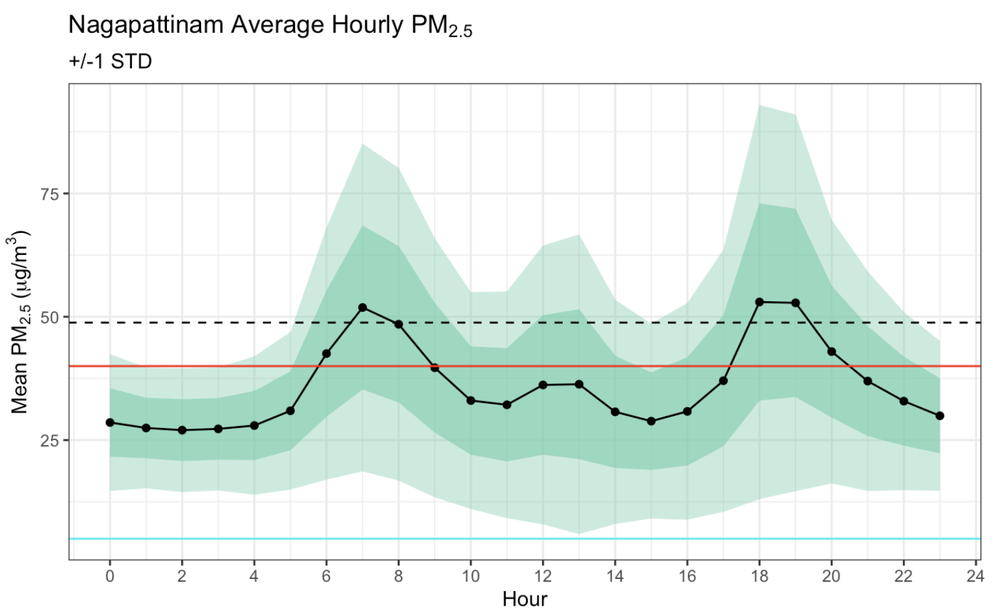
Data Analysis



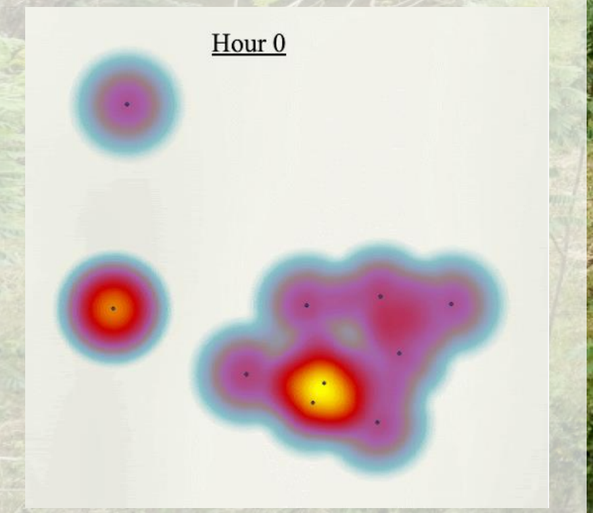
Nangudi, Tamil Nadu, India

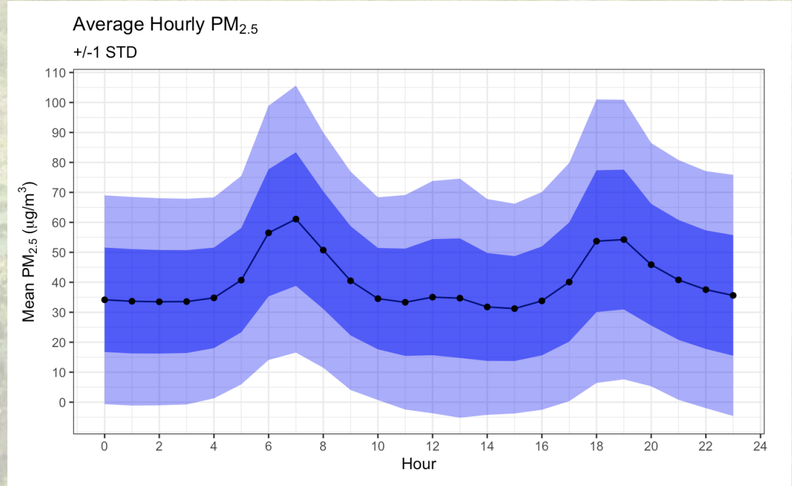
Hourly Fluctuations





India PM2.5 Standard
Annual Average
WHO Standard

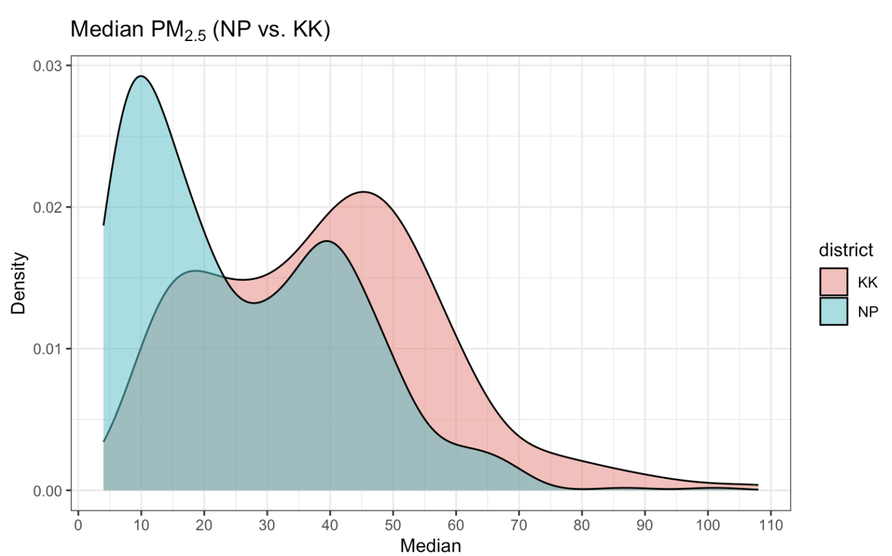


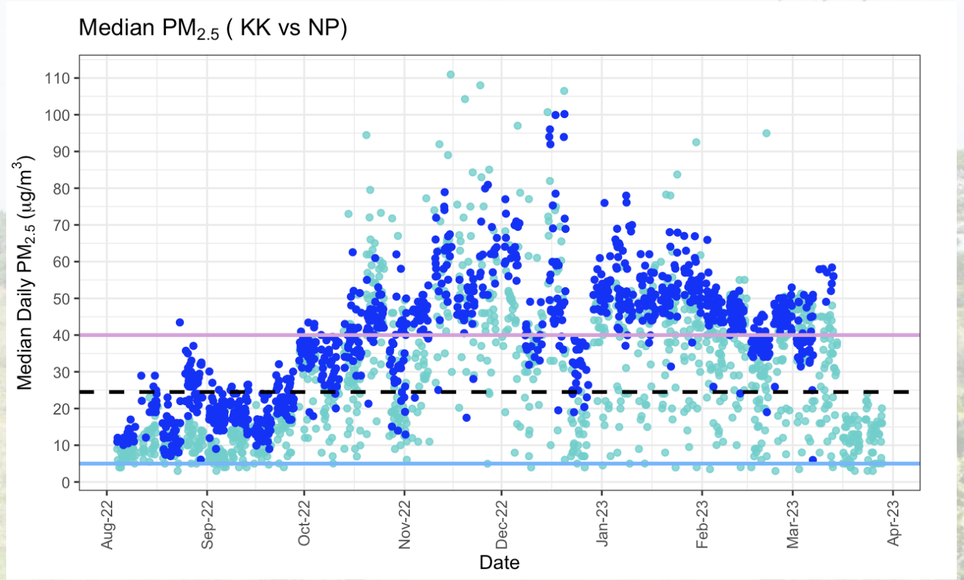


- Observed peaks during **cooking times**
  - Varies by district
- Generated **hourly heatmap** in ArcGIS Pro
  - Spatial temporal distribution of $PM_{2.5}$ concentration

Nangudi, Tamil Nadu, India

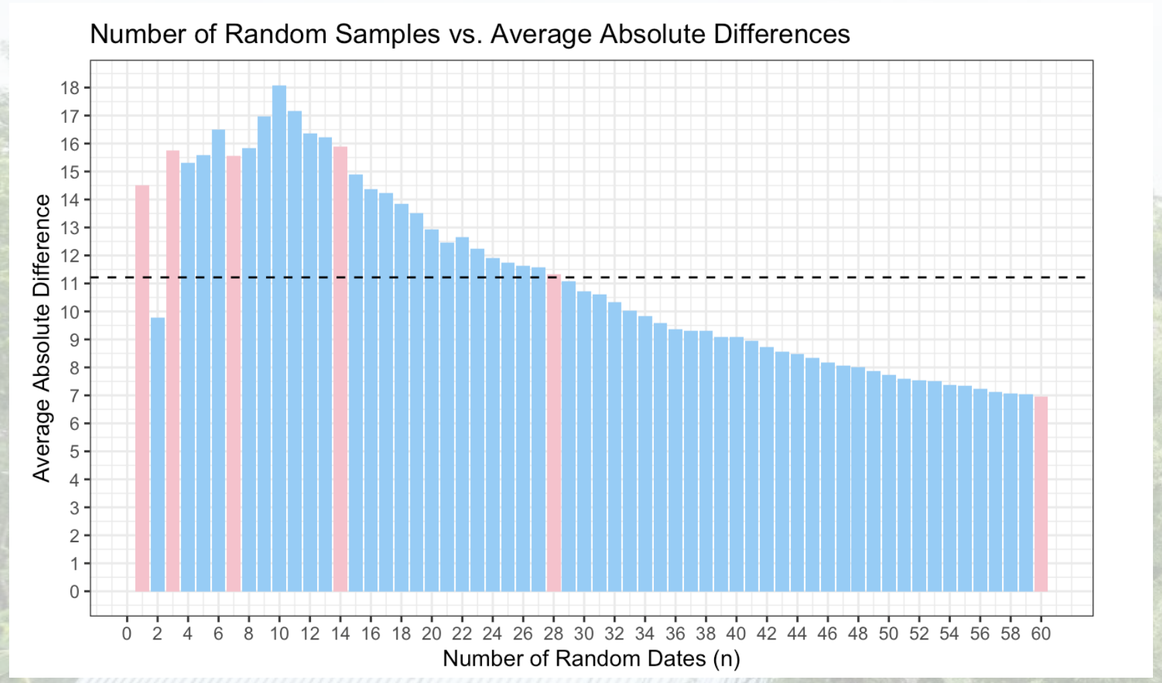
Comparing Districts





Mavilangai, Tamil Nadu, India

Sampling Analysis

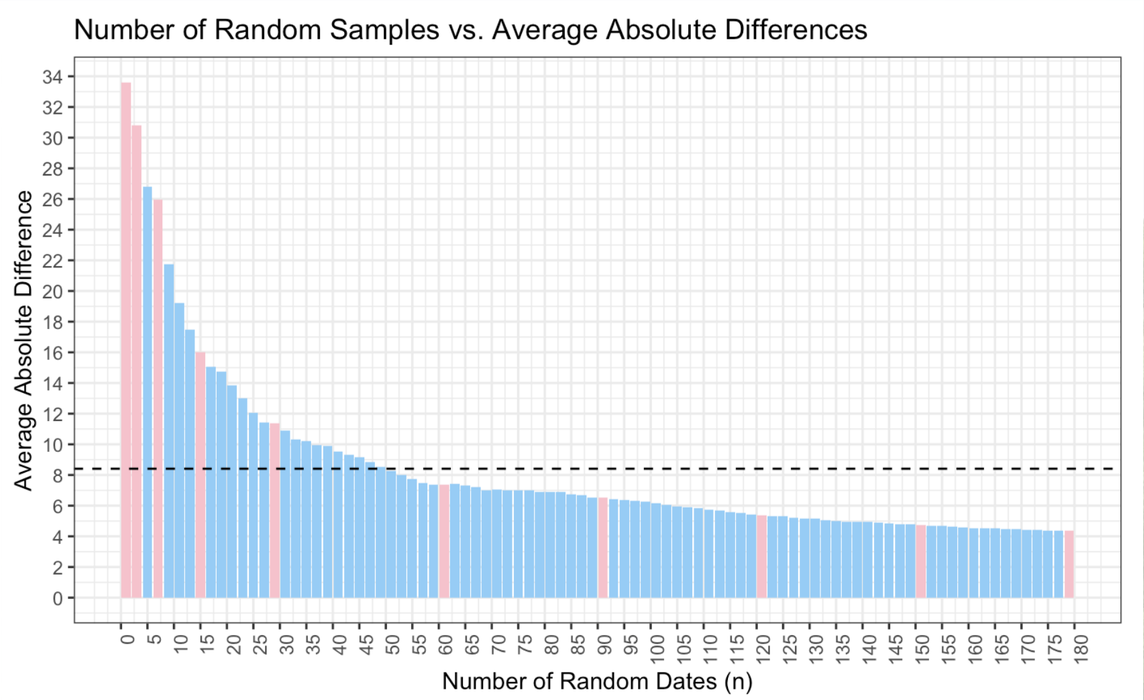


Random Sampling of Days

- Took one sensor from one habitation
- Randomly sampled (1, 2, … n) number of days
- Calculated distance from overall mean

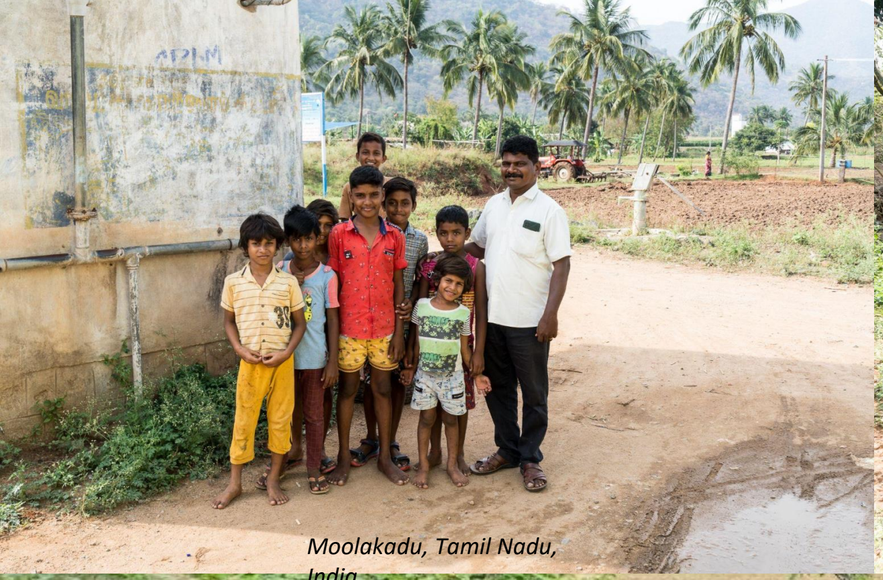
How does the distance from the overall $PM_{2.5}$ mean change when we randomly sample one day? Two? One week? Etc.

Sampling Analysis (cont.)



Expanded Random Sampling up to 180 Days

- Trend: variability from mean decreases as sample days increase



Moolakadu, Tamil Nadu, India

Mealvenniur, Tamil Nadu, India

Thronkoor, Tamil Nadu, India

Limitations and Future Work

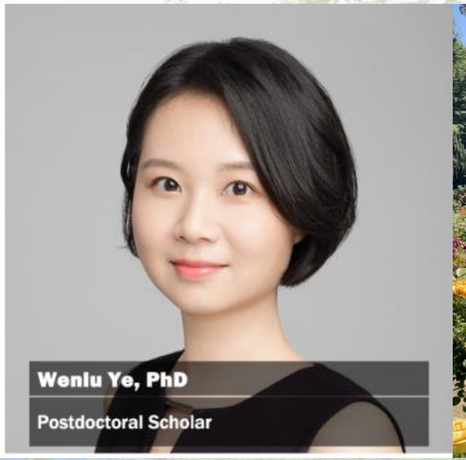
Limitations:

- Data gaps: missing aerogram (sd card) data cannot be recovered
  - Atmos (cloud) data can potentially be recovered
- Low cost sensors need to be calibrated to be 100% accurate, but overall $PM_{2.5}$ trends should remain the same

Future Work:

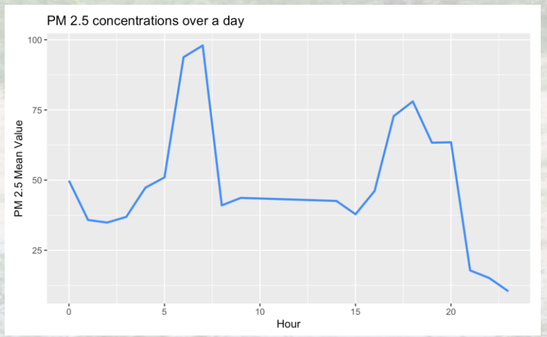
- Analysis of primary and secondary cookstoves.
- Continue sampling analysis to determine number of sensors needed.
- Using ambient air monitoring to measure the transition of households to clean fuels.

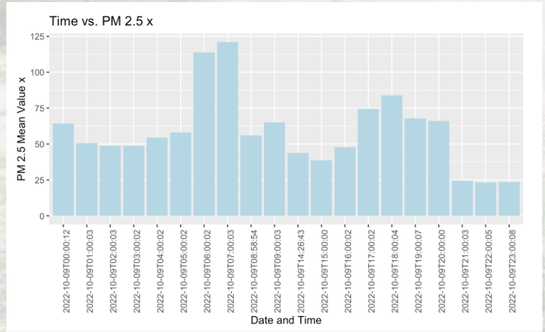
Team thanks!



householdenergy.org

Learned a lot this summer! :)
→ my first graphs:





With support from:
The STEER Team—Jesús Alfaro, Sadie Costello, Norma Firestone, Gina Grayson, Carisa Harris
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