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# Integrating Time-Activity, Air Quality Sensors and Models into Smartphone-based PM2.5 and Ozone Exposure Model


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**CMAS Meeting**
**October 2021**

United States Environmental Protection Agency

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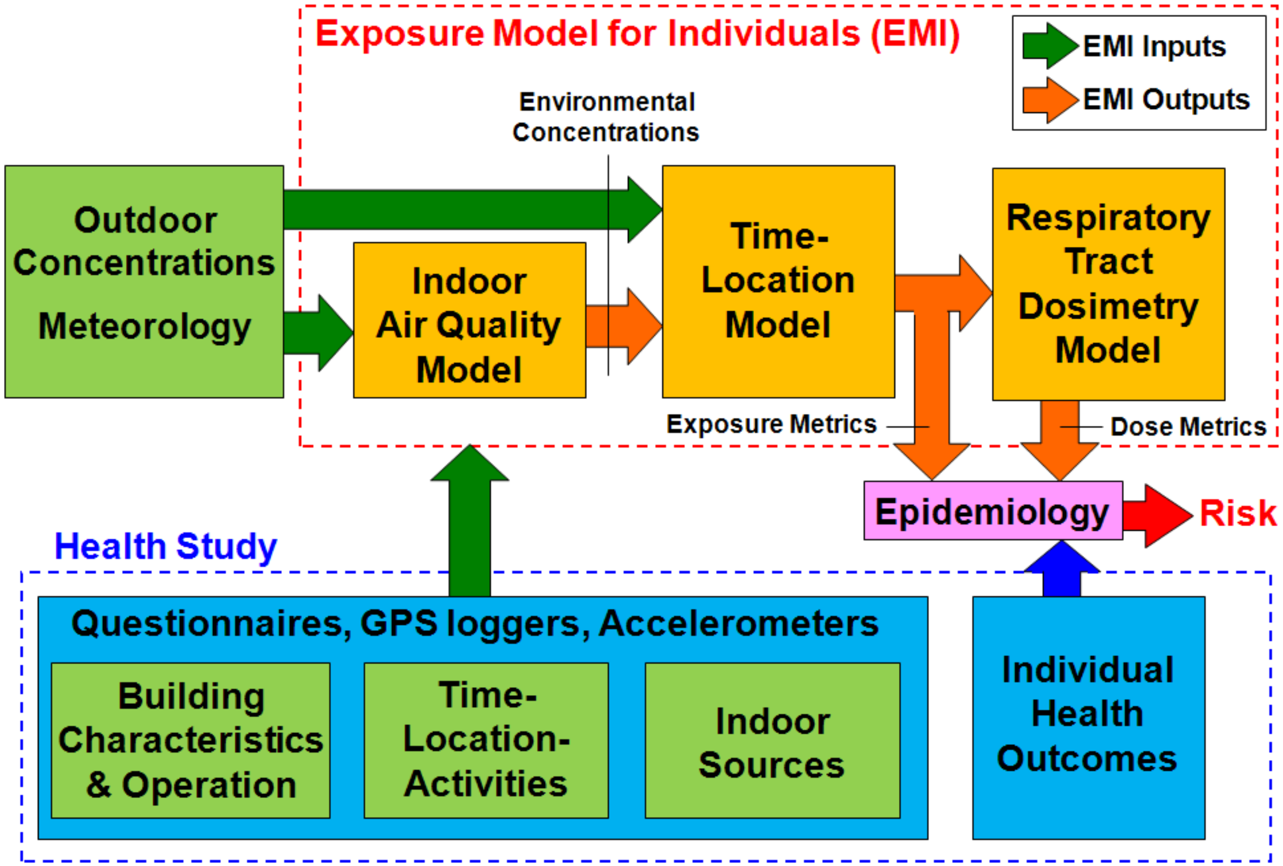
# Science Question & Relevance

- Science Question
  - Can individual-level exposure models integrated with wearable sensor technologies (e.g., GPS, accelerometers, smartphones):
    - Improve exposure assessments in risk estimates for epidemiology studies, which often rely on central-site air monitors?
    - Provide near real-time exposures for public health applications that allow people to modify their behavior and reduce their exposures (i.e., exposure management)?
- Relevance
  - Supports recommendations of NRC report (*Exposure Science in 21st Century*) and NAS report (*Using 21st Century Science to Improve Risk-Related Evaluations*) to integrate models with "big data" from wearable sensors to improve exposure assessments

# Exposure Model for Individuals (EMI)




**EMI evaluated with comprehensive field study data**



Breen et al., Environ. Sci. Technol. 2015.

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# Applications of EMI for Epidemiology

- EMI accounts for (1) time- and building-specific attenuation of ambient air pollutants, (2) time spent in different microenvironments (e.g., outdoors and indoors at home, work, school; in-vehicles), (3) physical activity-based inhalation rates
- EMI applied for multiple air pollution epidemiological studies:
  - DEPS – Type 2 diabetes cohort in central North Carolina
  - NEXUS – Asthmatic children in Detroit, Michigan
  - CADEE – Coronary artery disease cohort in central North Carolina
  - PISCES – Protective effects of fish oil in central North Carolina
  - MESA-Air – Cardiovascular study in multiple cities across US
  - CATHGEN – Coronary artery disease cohort in 3 NC counties

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# TracMyAir Smartphone App

**Research exposure model that runs on smartphones to facilitate and expand use of exposure metrics for epidemiological studies**

EPA www.epa.gov/research

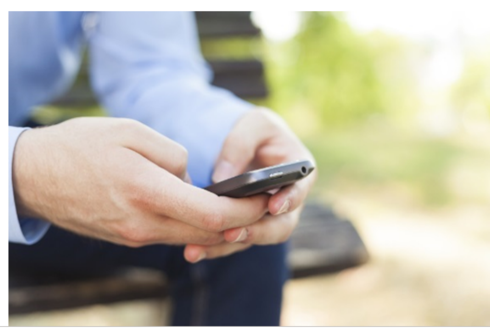
science in ACTION

INNOVATIVE RESEARCH FOR A SUSTAINABLE FUTURE

**EPA's TracMyAir App: Using smart phones to predict near real-time air pollution exposures**

**Background**

To better understand people's contact with air pollutants and their potential for adverse health effects, it's important to estimate how much time they spend in different locations and what the air pollutant concentrations are in those locations. Using currently available personal air monitors to collect this information has several limitations, including burden on participants, cost, and need for substantial technical expertise.



International Journal of *Environmental Research and Public Health*

MDPI

*Article*

## Development of TracMyAir Smartphone Application for Modeling Exposures to Ambient $PM_{2.5}$ and Ozone

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Received: 1 August 2019; Accepted: 15 September 2019; Published: 18 September 2019

check for updates

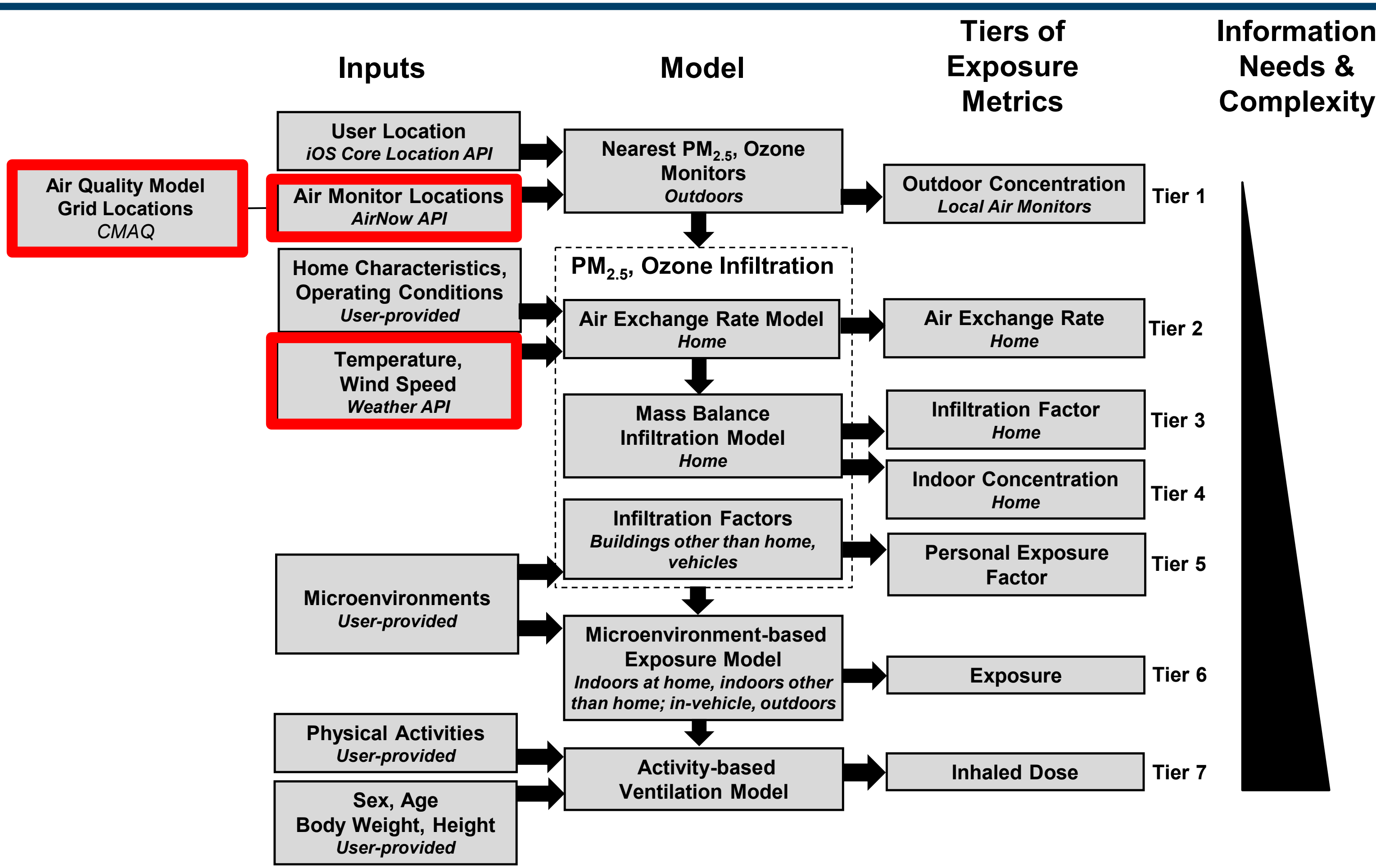
**Abstract:** Air pollution epidemiology studies of ambient fine particulate matter ($PM_{2.5}$) and ozone ($O_3$) often use outdoor concentrations as exposure surrogates. Failure to account for the variability of the indoor infiltration of ambient $PM_{2.5}$ and $O_3$, and time indoors, can induce exposure errors. We developed an exposure model called TracMyAir, which is an iPhone application ("app") that determines seven tiers of individual-level exposure metrics in real-time for ambient $PM_{2.5}$ and $O_3$ using outdoor concentrations, weather, home building characteristics, time-locations, and time-activities. We linked a mechanistic air exchange rate (AER) model, a mass-balance $PM_{2.5}$ and $O_3$ building infiltration model, and an inhaled ventilation model to determine outdoor concentrations (Tier 1), residential AER (Tier 2), infiltration factors (Tier 3), indoor concentrations (Tier 4), personal exposure factors (Tier 5), personal exposures (Tier 6), and inhaled doses (Tier 7). Using the application in central North Carolina, we demonstrated its ability to automatically obtain real-time input data from the nearest air monitors and weather stations, and predict the exposure metrics. A sensitivity analysis showed that the modeled exposure metrics can vary substantially with changes in seasonal indoor-outdoor temperature differences, daily home operating conditions (i.e., opening windows and operating air cleaners), and time spent outdoors. The capability of TracMyAir could help reduce uncertainty of ambient $PM_{2.5}$ and $O_3$ exposure metrics used in epidemiology studies.

**Breen et al., Int J Environ Res Public Health. 2019**

# TracMyAir Features

- Accounts for user's location to obtain input data from nearest $PM_{2.5}$ and ozone monitors, weather stations
- Accounts for variability of home air exchange rate due to building characteristics, weather, open windows, window fans
- Includes removal of PM2.5 from home air cleaners
- Accounts for time spent in different indoor microenvironments (indoors at home, work, in-vehicle) to determine microenvironment-based exposures
- Accounts for time spent at different physical activity levels to determine inhaled dose
- Designed for non-technical users (e.g., study participants, health clinicians)

# Inputs from Air Monitors + Models & Weather Stations






Breen et al., Int J Environ Res Public Health. 2019

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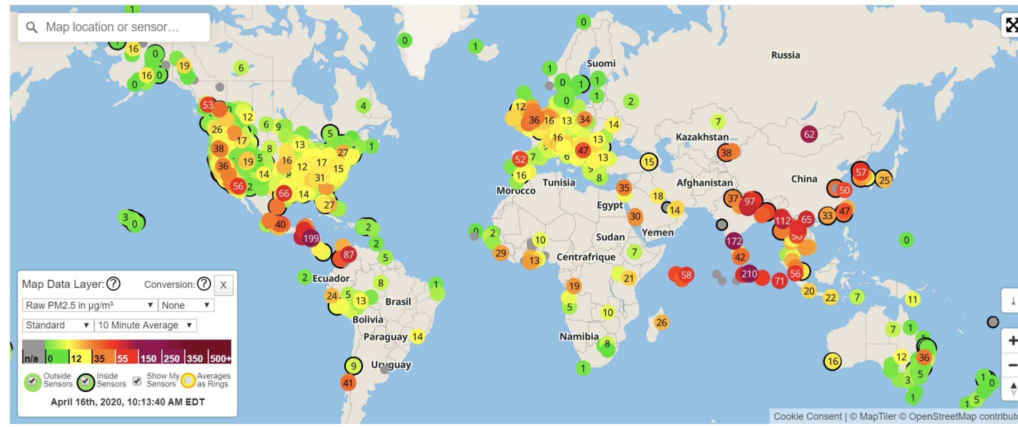
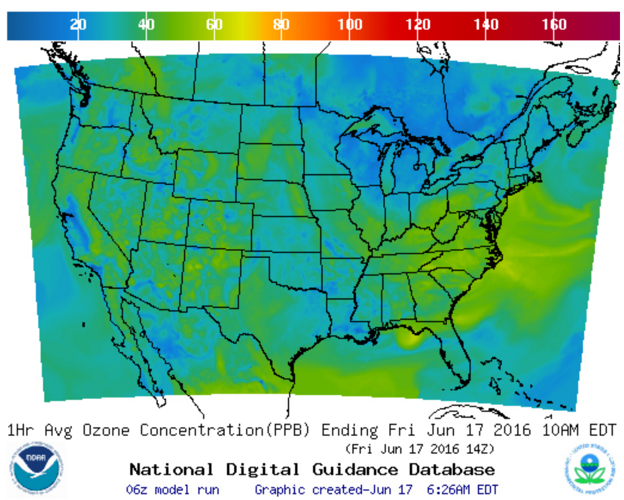
# Inputs from Air Monitors and Models


**Official monitor networks: AirNow, OpenAQ ($PM_{2.5}$, $O_3$)**




**Low cost sensor networks: PurpleAir ($PM_{2.5}$)**




**Models: CMAQ v5.1 ($PM_{2.5}$, $O_3$ Interpolated Dissemination Product at 5x5-km grid, 1-hr avg.)**

**Source: NOAA's National Air Quality Forecasts**

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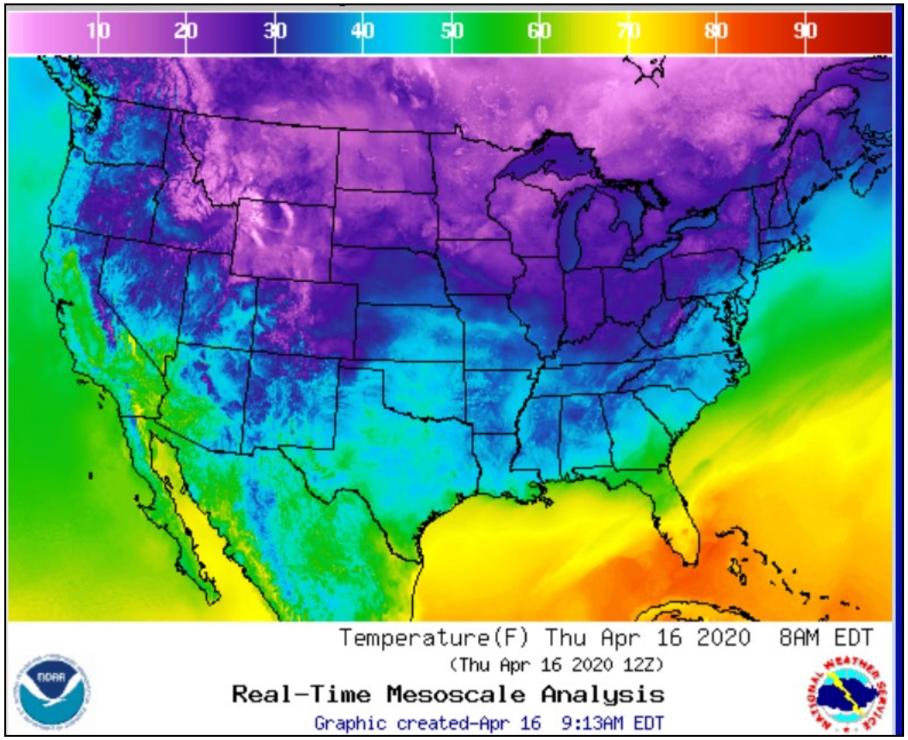
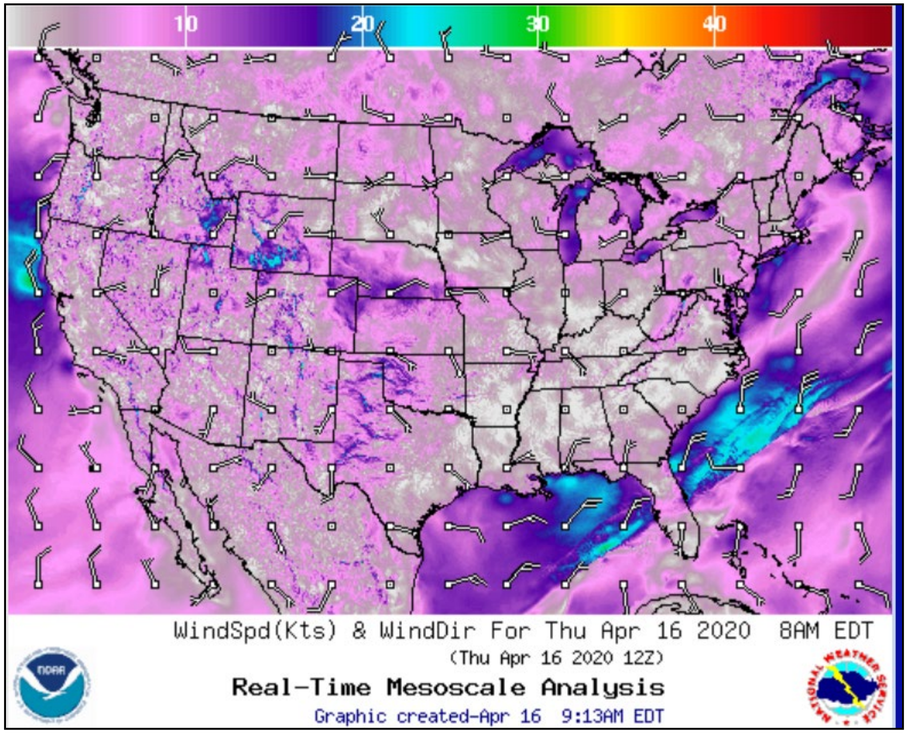
# Input Data from Weather Stations

**Temperature**



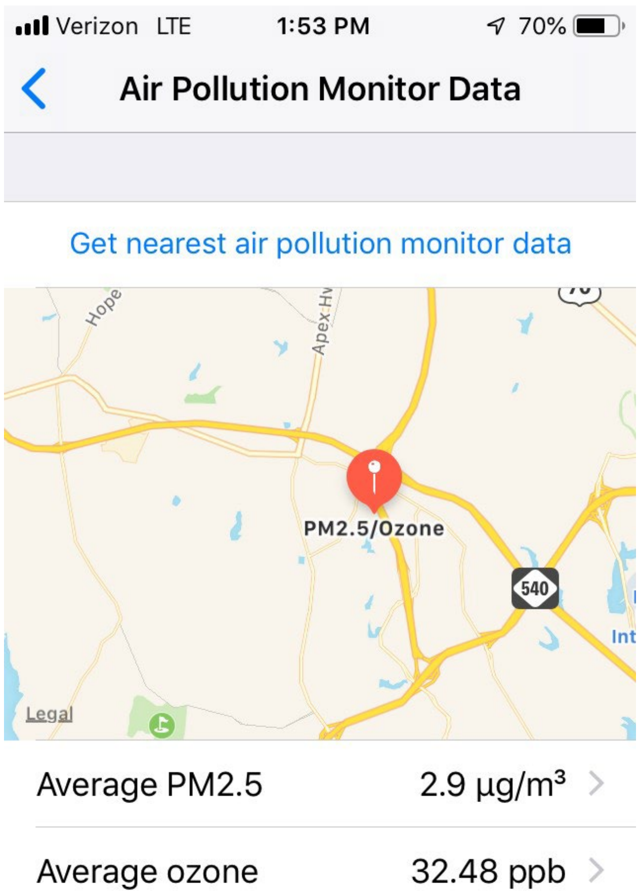

**Wind speed**

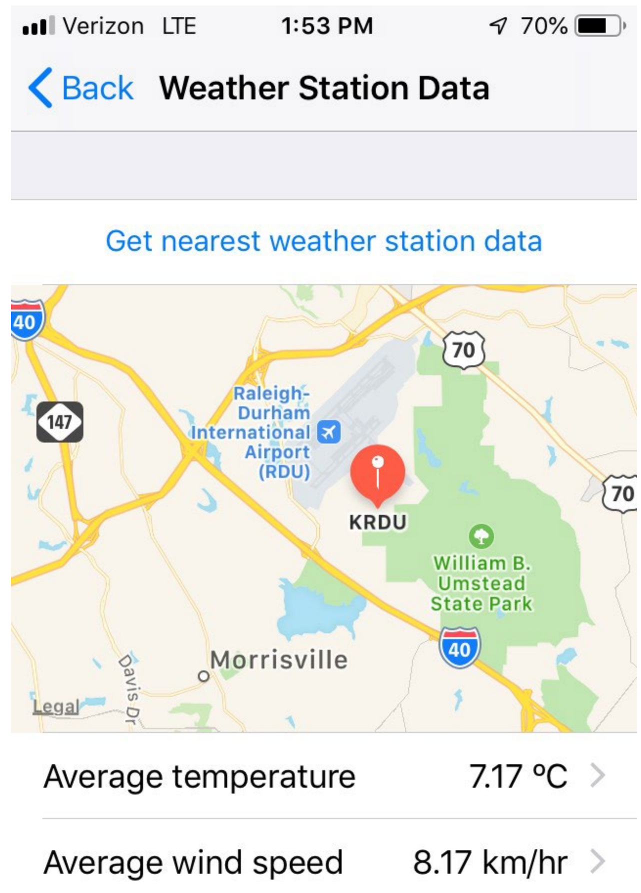



**Weather.gov – US network of weather stations**

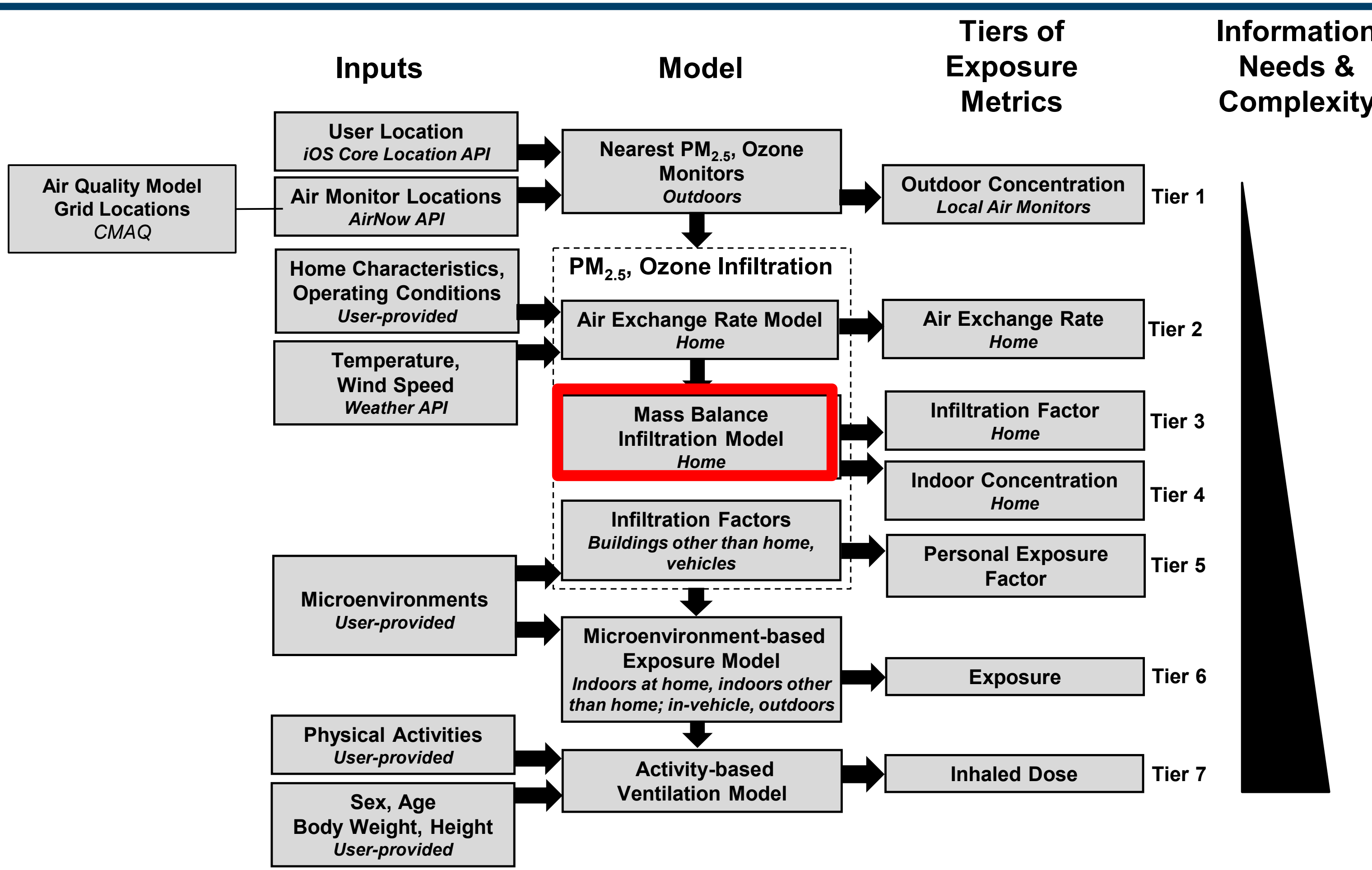
**Temperature, wind speed are used to determine residential air exchange rates**

# TracMyAir: Automated Real-time Input Data



# Building Infiltration Model

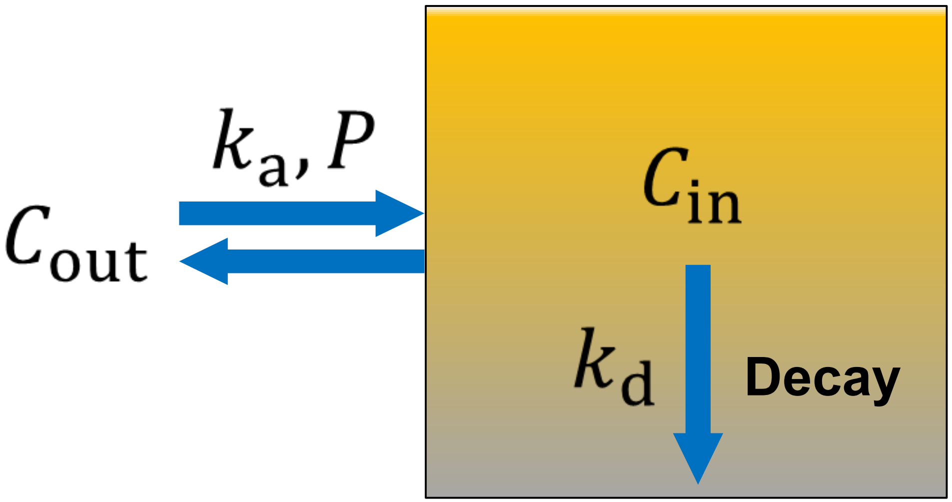





Breen et al., Int J Environ Res Public Health. 2019

# Home Infiltration Model

**Single Compartment Model**




**Infiltration factor**

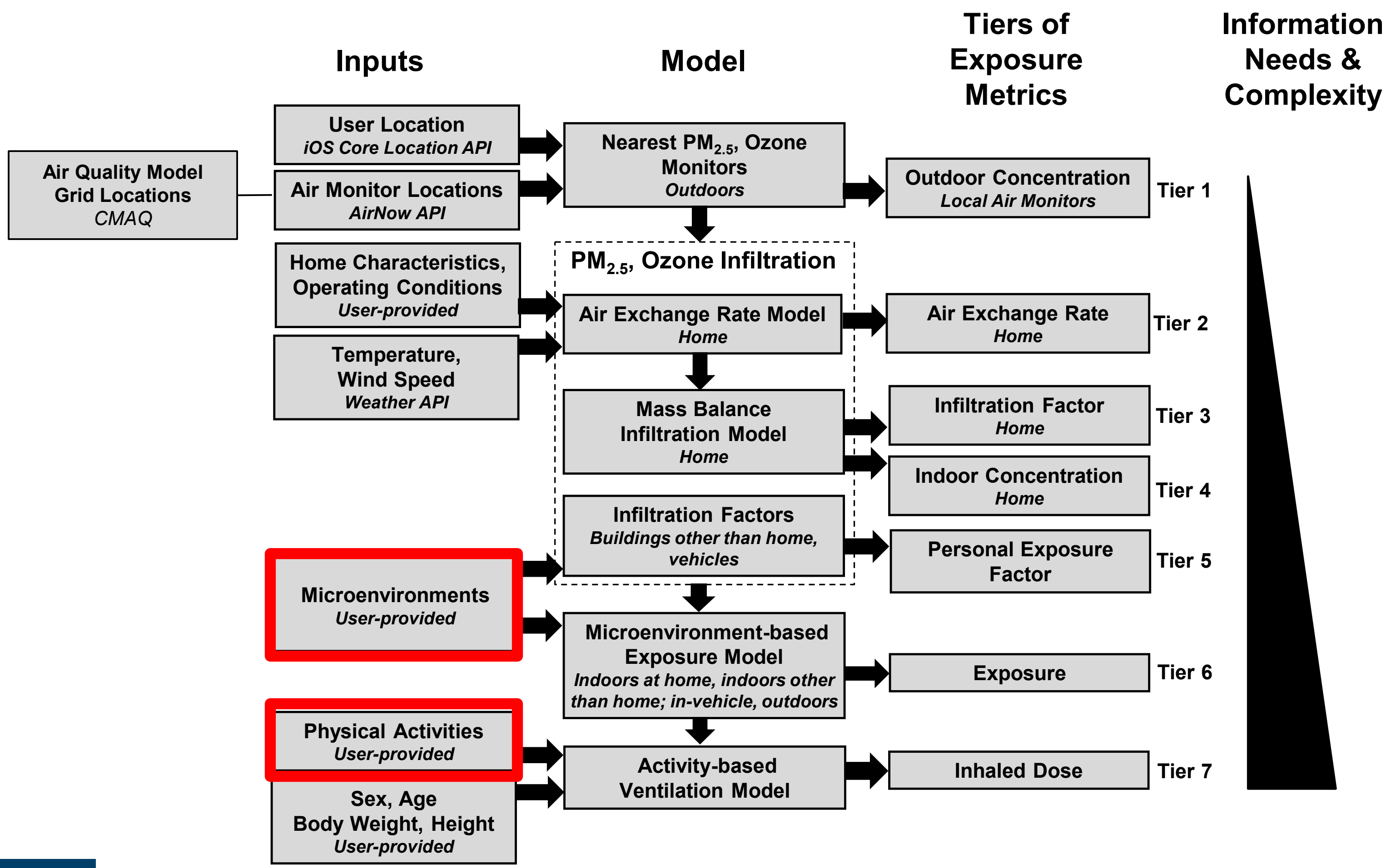
$$C_{in} = \overbrace{\frac{k_a P}{k_a + k_d}}^{\text{Infiltration factor}} C_{out}$$

**Infiltration factor accounts for indoor attenuation of outdoor concentration**



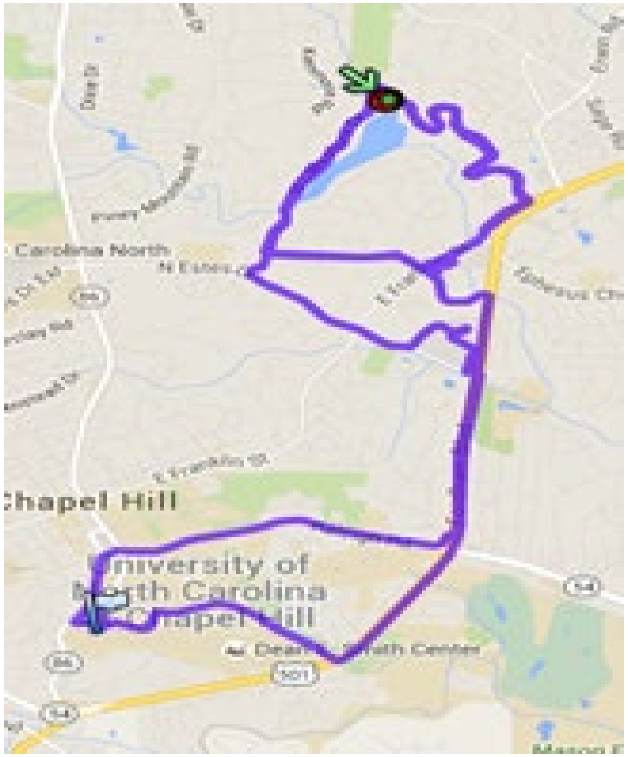
Breen et al., Environ. Sci. Technol. 2015.

# Inputs from Smartphone Sensors




Breen et al., Int J Environ Res Public Health. 2019

# Input Data from Wearable Sensors




User's location tracks from smartphone location services (e.g., GPS)


User's physical activity levels from smartphone or smartwatch motion sensors (e.g., accelerometer)

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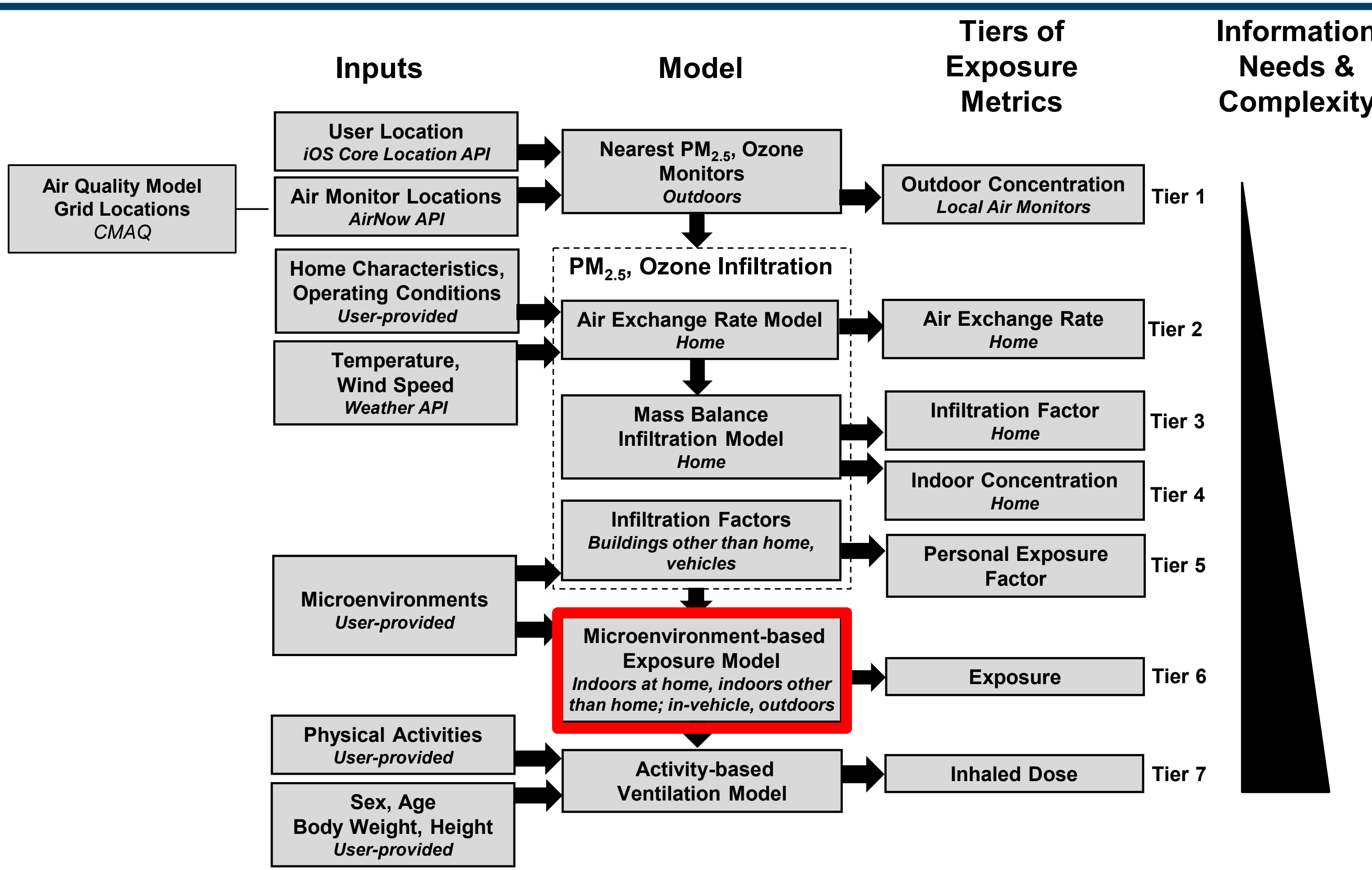
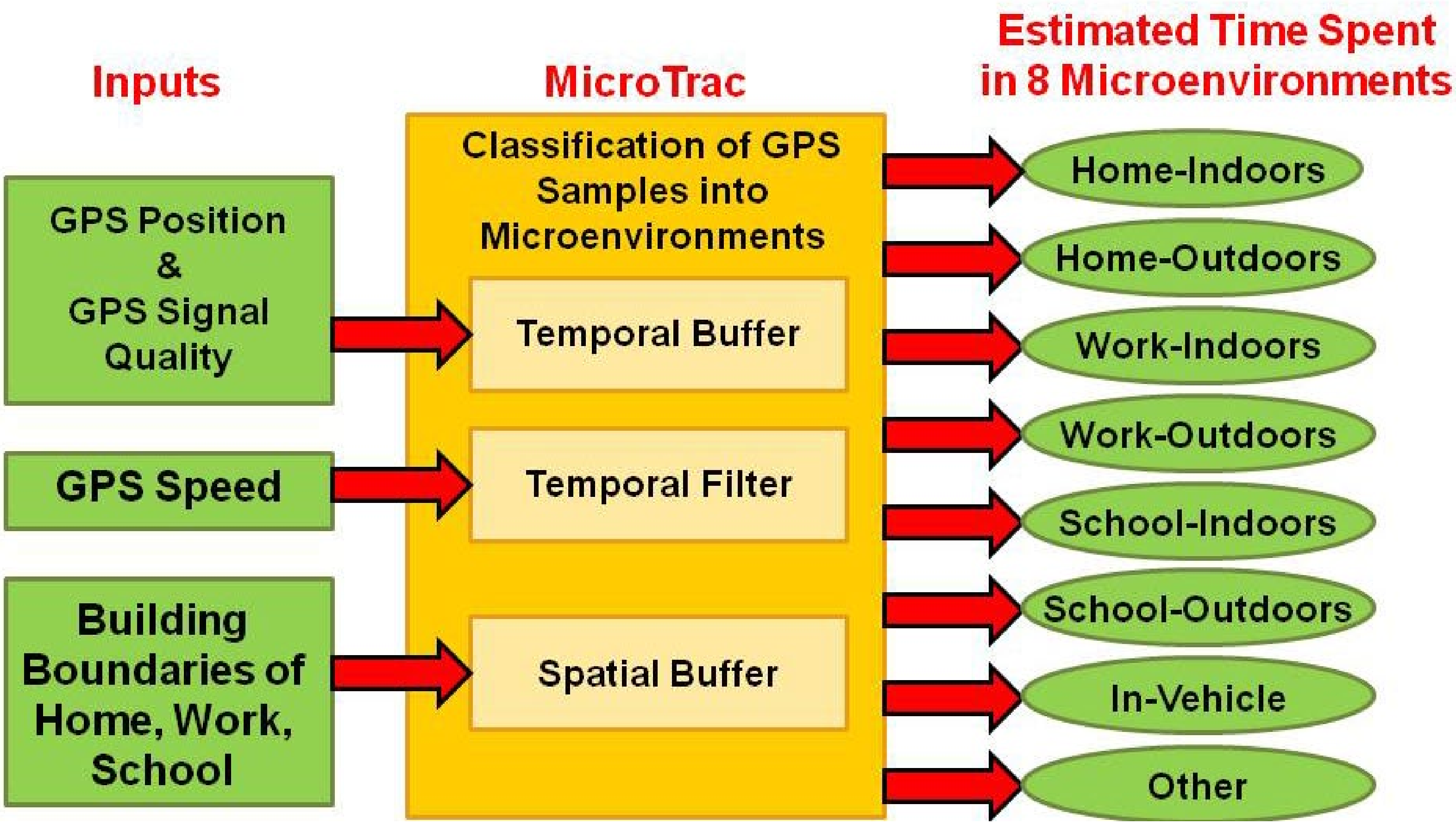
# Microenvironment Tracker (MicroTrac) Model






Breen et al., Int J Environ Res Public Health. 2019

# MicroTrac Model






Breen et al., J. Exp. Sci. Environ. Epidemiol. 2014

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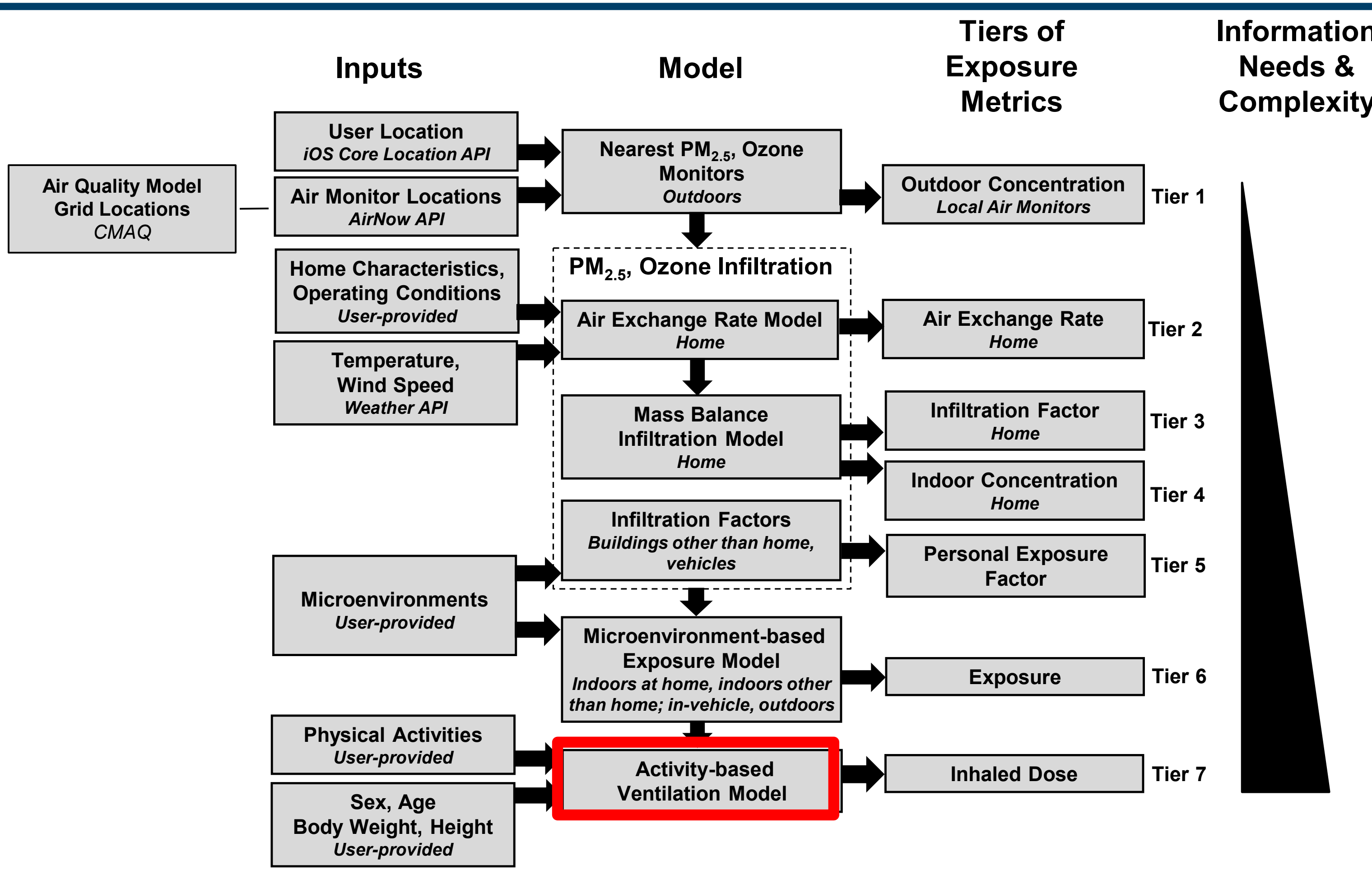
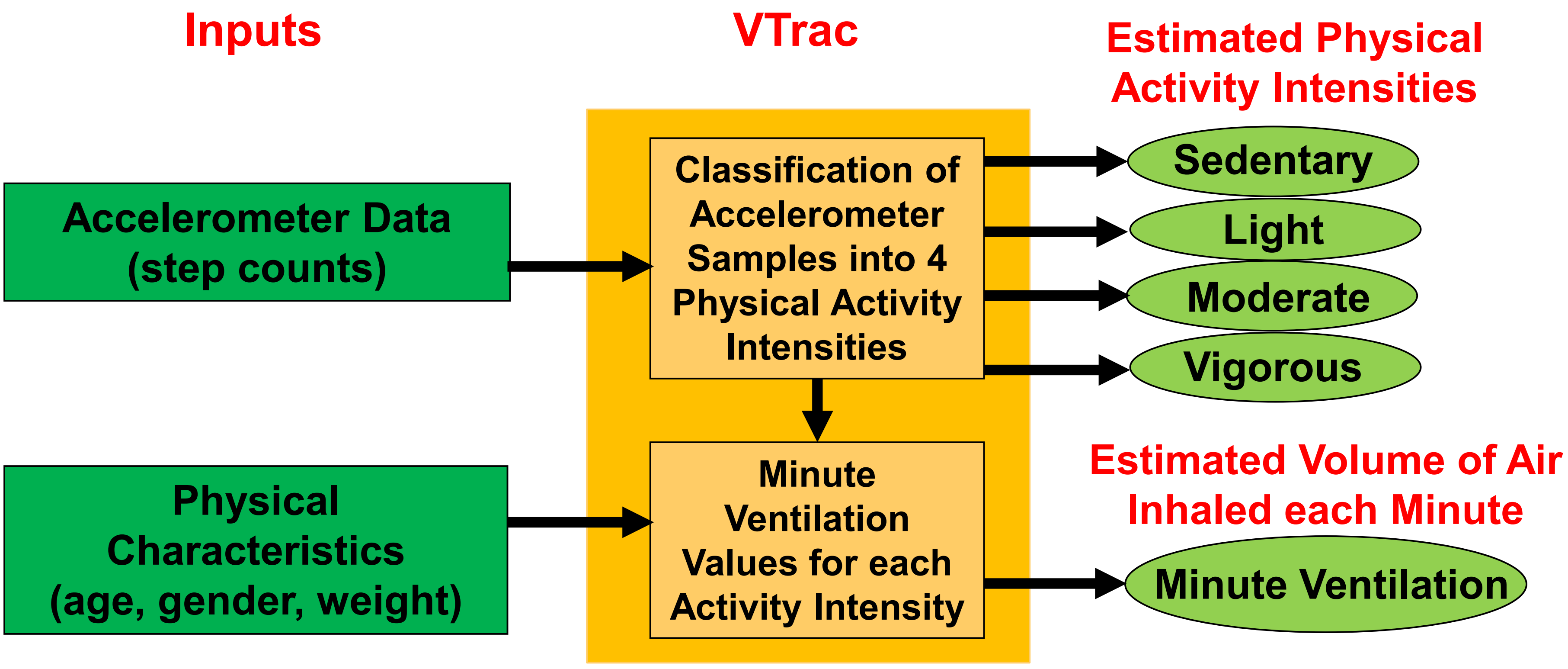
# Ventilation Tracker (VTrac) Model






Breen et al., Int J Environ Res Public Health. 2019

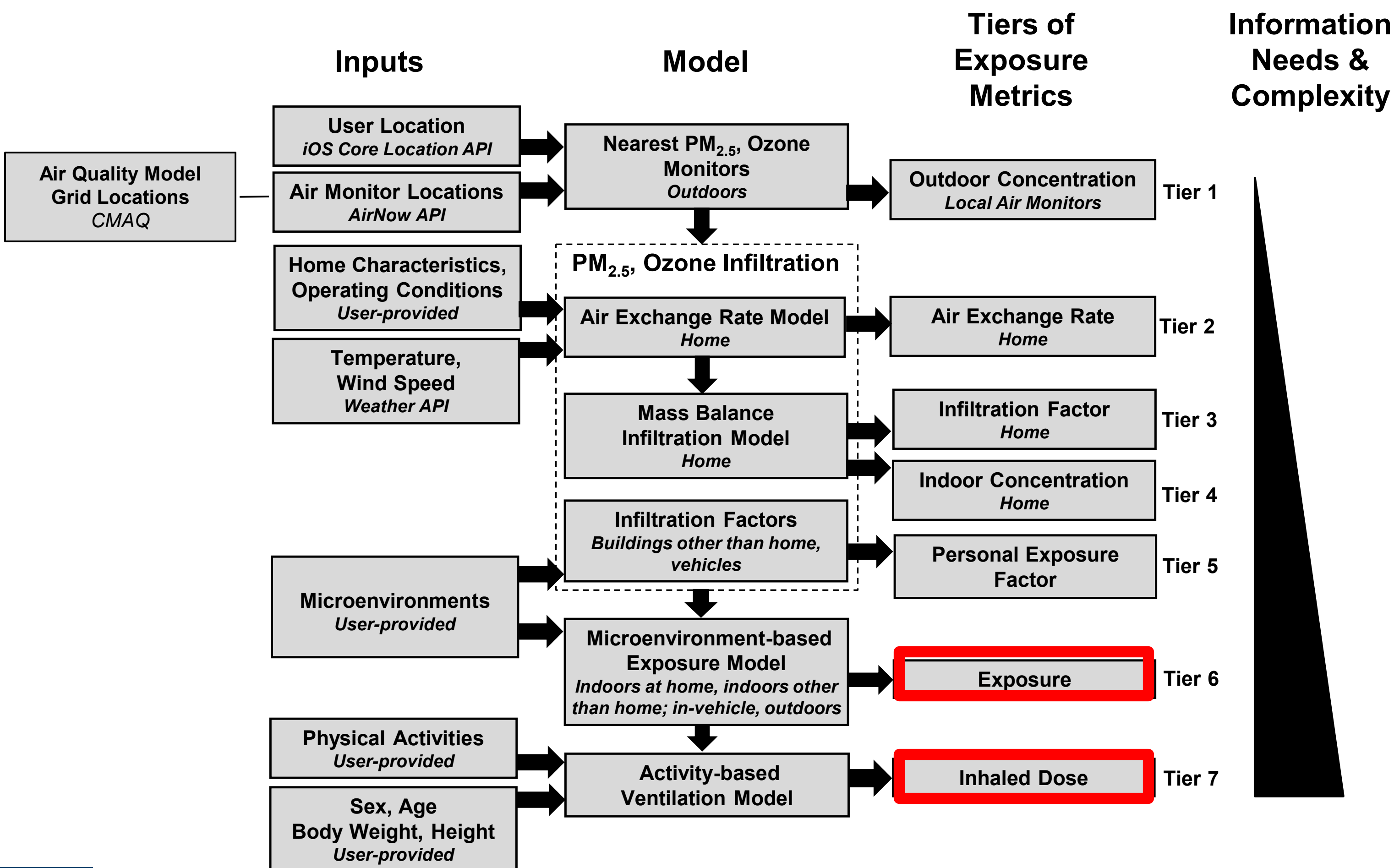
# VTrac Model






Breen et al., Int J Environ Res Public Health. 2019

# TracMyAir Outputs




Breen et al., Int J Environ Res Public Health. 2019

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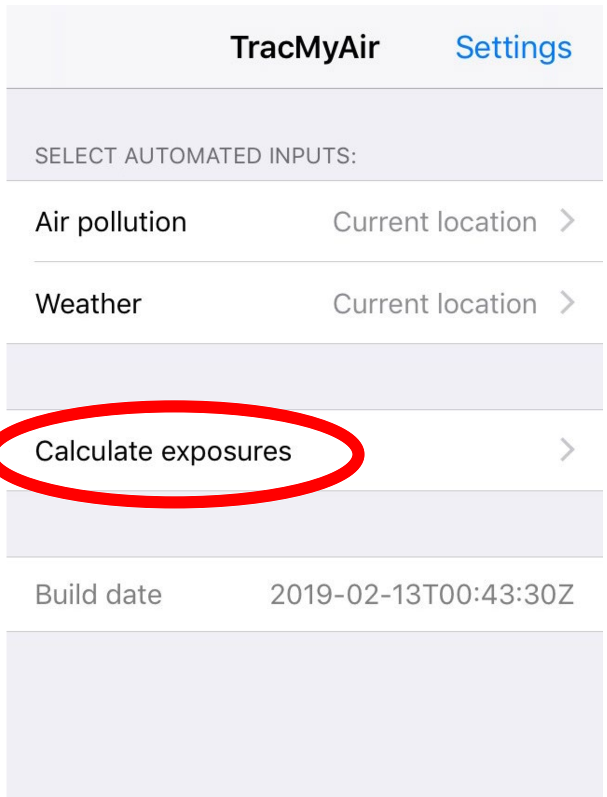
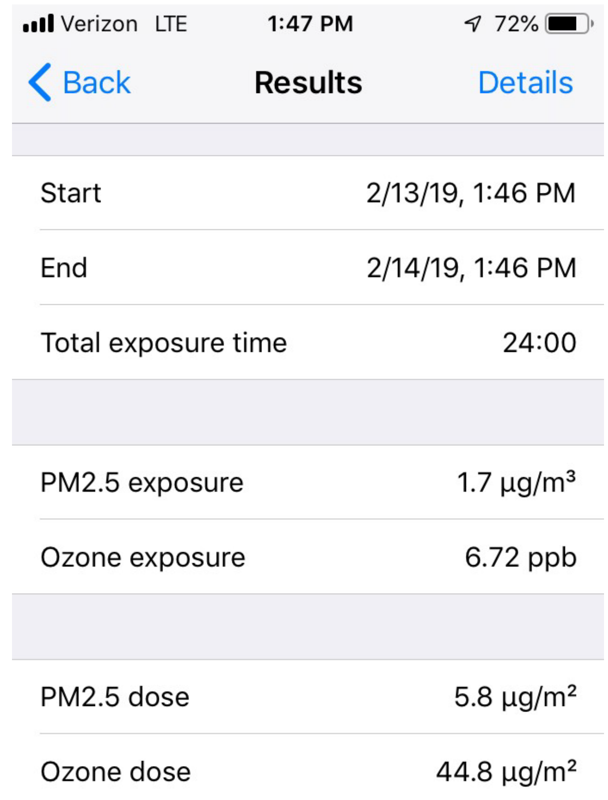
# Running TracMyAir: Outputs (24 h avg)




Main App Screen




**(Mass/body surface area)**

Outputs

App execution time: 5-10 s

# TracMyAir: Exposure/Dose for Each Microenvironment

Verizon 2:12 PM 50%

**Back — Indoors at home**

| | |
|---|---|
| Time spent indoors at home | 13:15 / 55.21% |
| PM2.5 exposure | 3.2 µg/m$^3$ / 48.01% |
| PM2.5 dose | 19.7 µg/m$^2$ / 33.55% |
| Ozone exposure | 1.32 ppb / 27.94% |
| Ozone dose | 16.2 µg/m$^2$ / 11.62% |

Verizon 2:12 PM 51%

**Back — Outdoors**

| | |
|---|---|
| Time spent outdoors | 1:30 / 6.25% |
| PM2.5 exposure | 0.7 µg/m$^3$ / 10.80% |
| PM2.5 dose | 19.7 µg/m$^2$ / 33.60% |
| Ozone exposure | 1.88 ppb / 39.74% |
| Ozone dose | 102.6 µg/m$^2$ / 73.56% |

Verizon 2:12 PM 50%

**Back — Inside vehicles**

| | |
|---|---|
| Time spent inside vehicles | 1:00 / 4.17% |
| PM2.5 exposure | 0.2 µg/m$^3$ / 3.17% |
| PM2.5 dose | 1.1 µg/m$^2$ / 1.83% |
| Ozone exposure | 0.29 ppb / 6.09% |
| Ozone dose | 2.9 µg/m$^2$ / 2.10% |

Verizon 2:13 PM 50%

**Back — Indoors at work**

| | |
|---|---|
| Time spent indoors at work | 7:45 / 32.29% |
| PM2.5 exposure | 2.3 µg/m$^3$ / 35.72% |
| PM2.5 dose | 14.9 µg/m$^2$ / 25.34% |
| Ozone exposure | 1.16 ppb / 24.64% |
| Ozone dose | 14.5 µg/m$^2$ / 10.40% |

- **TracMyAir provides daily exposure, dose for each ME, which can help design mitigation strategies**
- **For a test case, results show:**
  - **Most time spent indoors at home, which corresponds to highest PM2.5 exposure, dose**
  - **Less time spent outdoors, but highest ozone exposure, dose due to substantially higher ozone levels outdoors as compared to indoors**

# Acknowledgments


## Model Design & Evaluation Teams

EMI – Exposure Model for Individuals
AER – Residential air exchange rate
MicroTrac – Microenvironment Tracker
VTrac – Ventilation Tracker
TracMyAir – Smartphone App

## Epidemiology & Field Study Teams

RTP PM Panel Study
NEXUS – asthma cohort
DEPS – diabetes cohort
CADEE – cardiovascular disease cohort
MESA Air – arteriosclerosis cohort
PISCES – fish oil cohort
CATHGEN – coronary catheterization cohort
MASKOFF – protective mask for wood smoke

## EPA Collaborators

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