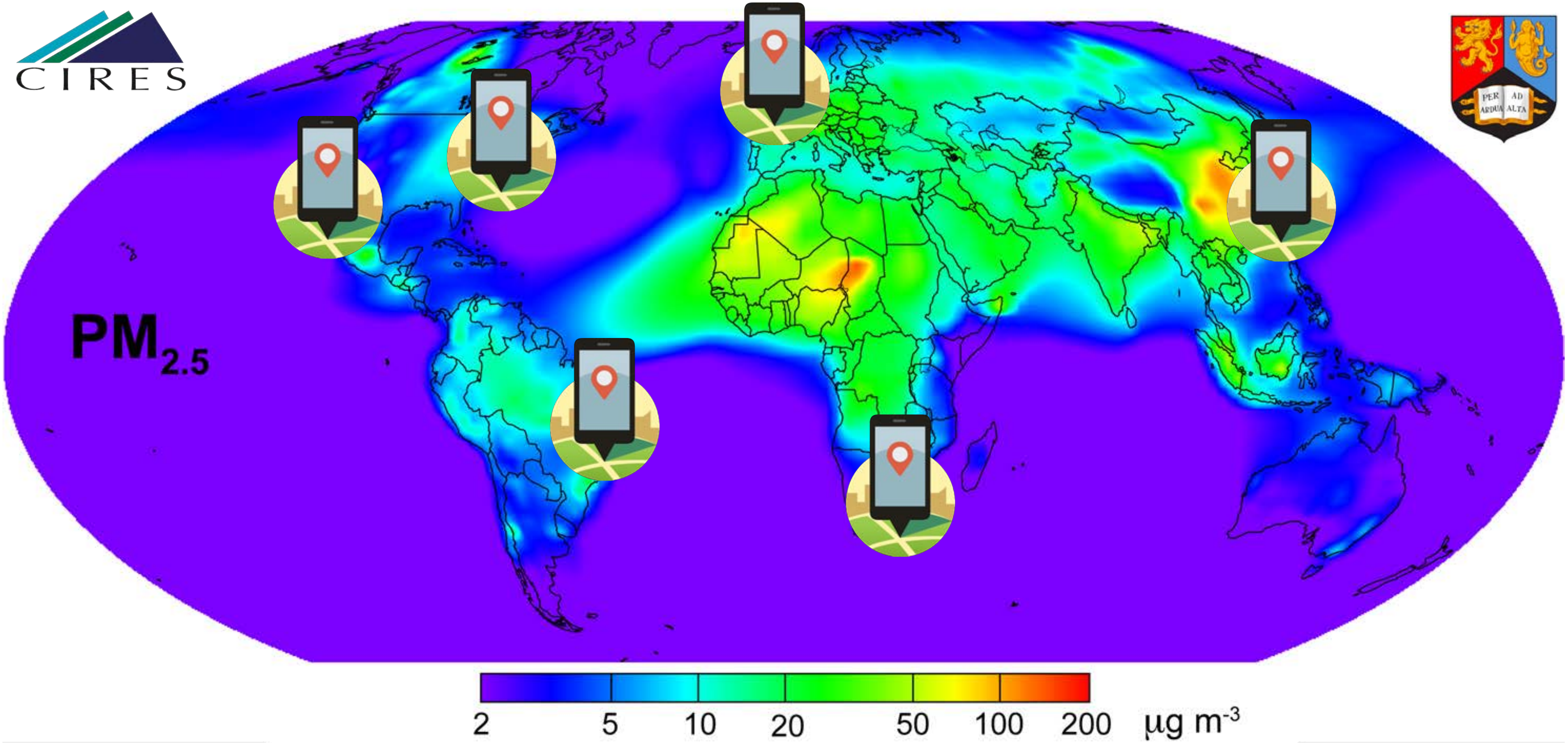
Using Google Location History to track personal exposure to air pollution



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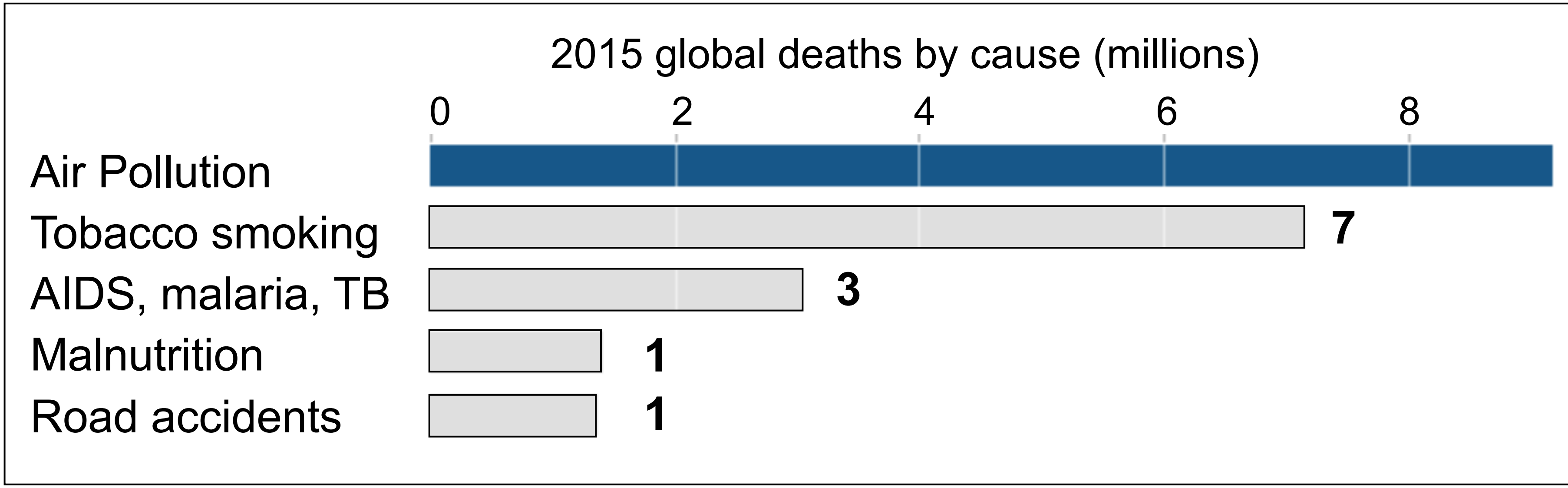
AGU, Session AS31N New Orleans, LA 13 December 2017

Air pollution now the top global health risk

Air pollution (mostly fine particles) is detrimental to health



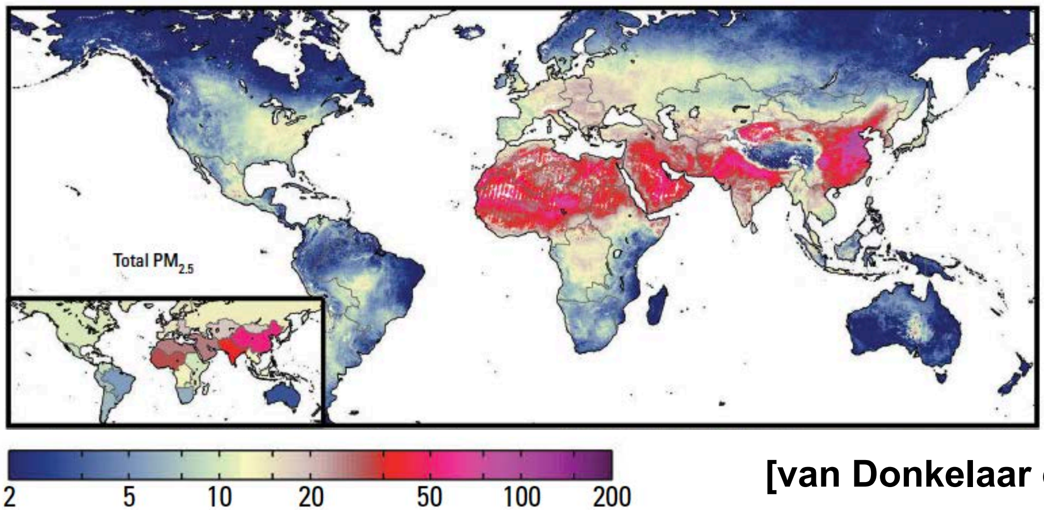
[Landrigan et al., 2017]

9 million premature deaths attributable to air pollution

Exposure estimates assume static interaction with air pollution

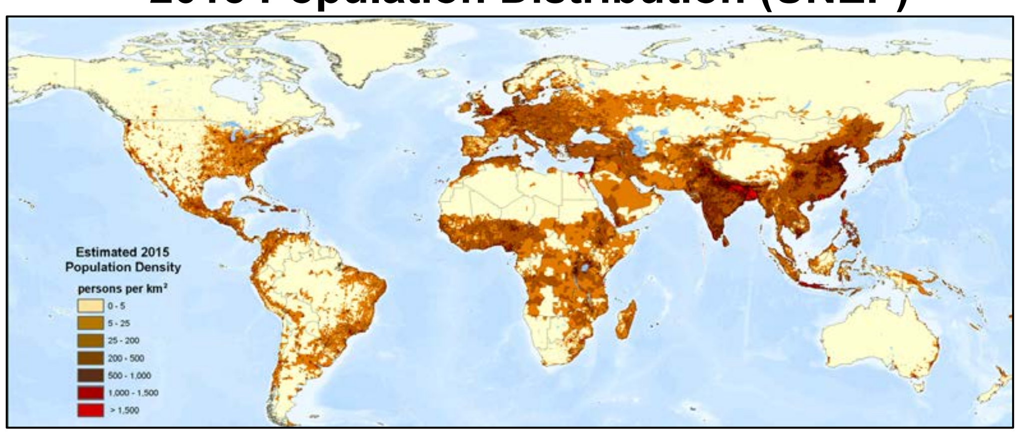
Population-weighted $PM_{2.5}$ estimated with **annual mean $PM_{2.5}$** and **population maps**

Multiyear (2001-2010) annual mean $PM_{2.5}$ ($\mu g\ m^{-3}$) from satellite AOD observations



[van Donkelaar et al., 2015]

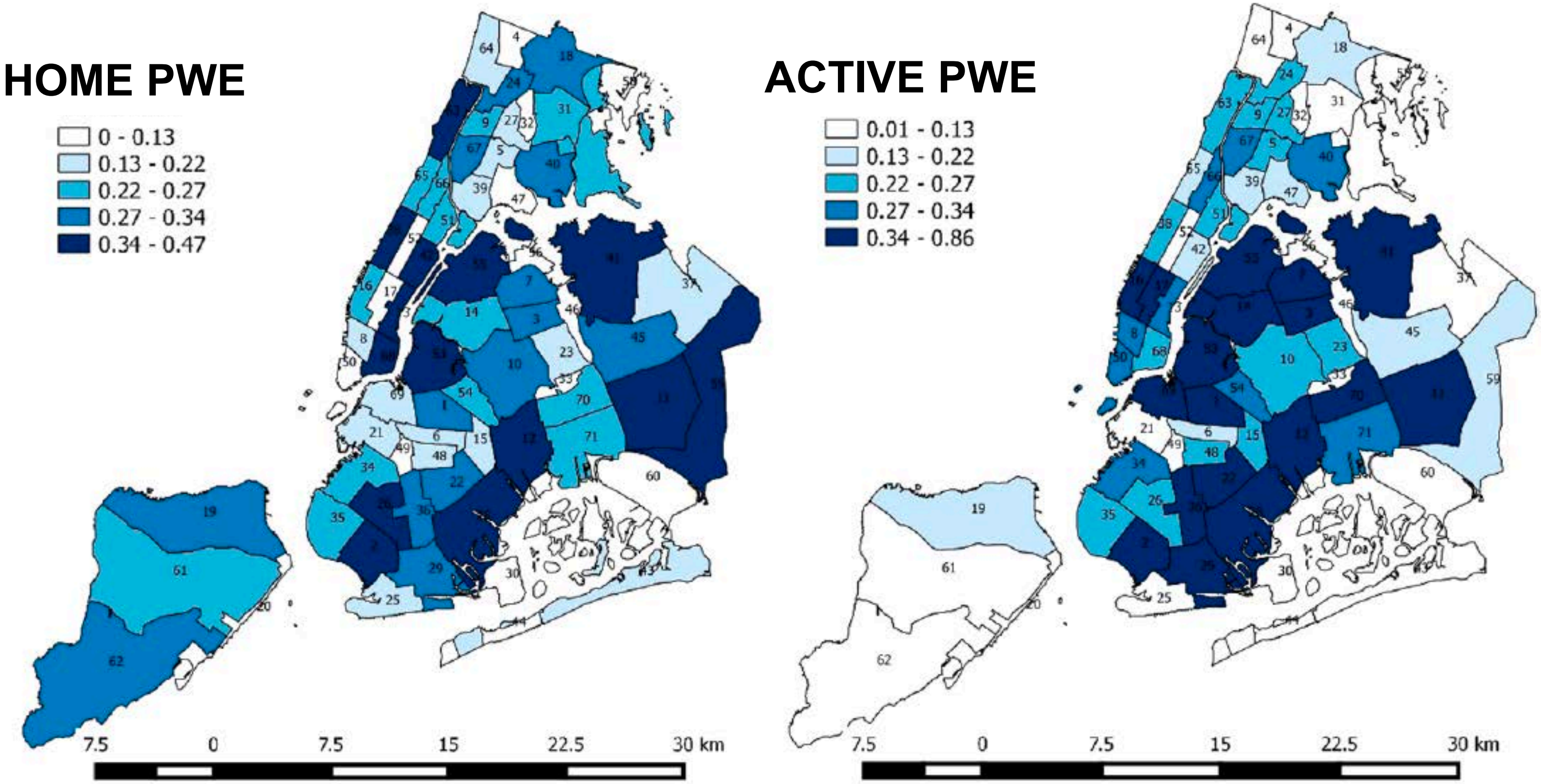
2015 Population Distribution (UNEP)



How representative is this of personal exposure in an increasingly mobile world?

Accounting for mobility has large effect on exposure estimate

$PM_{2.5}$ exposure estimated with urban monitoring network and either census data (**HOME**) or traffic data from mobile and wireless devices (**ACTIVE**)



[Nyhan et al., 2016]

PWE: population-weighted exposure to $PM_{2.5}$

Google Archive stores detailed location information

Indoors (hotel)

Commute

Outdoors (park)

Commute

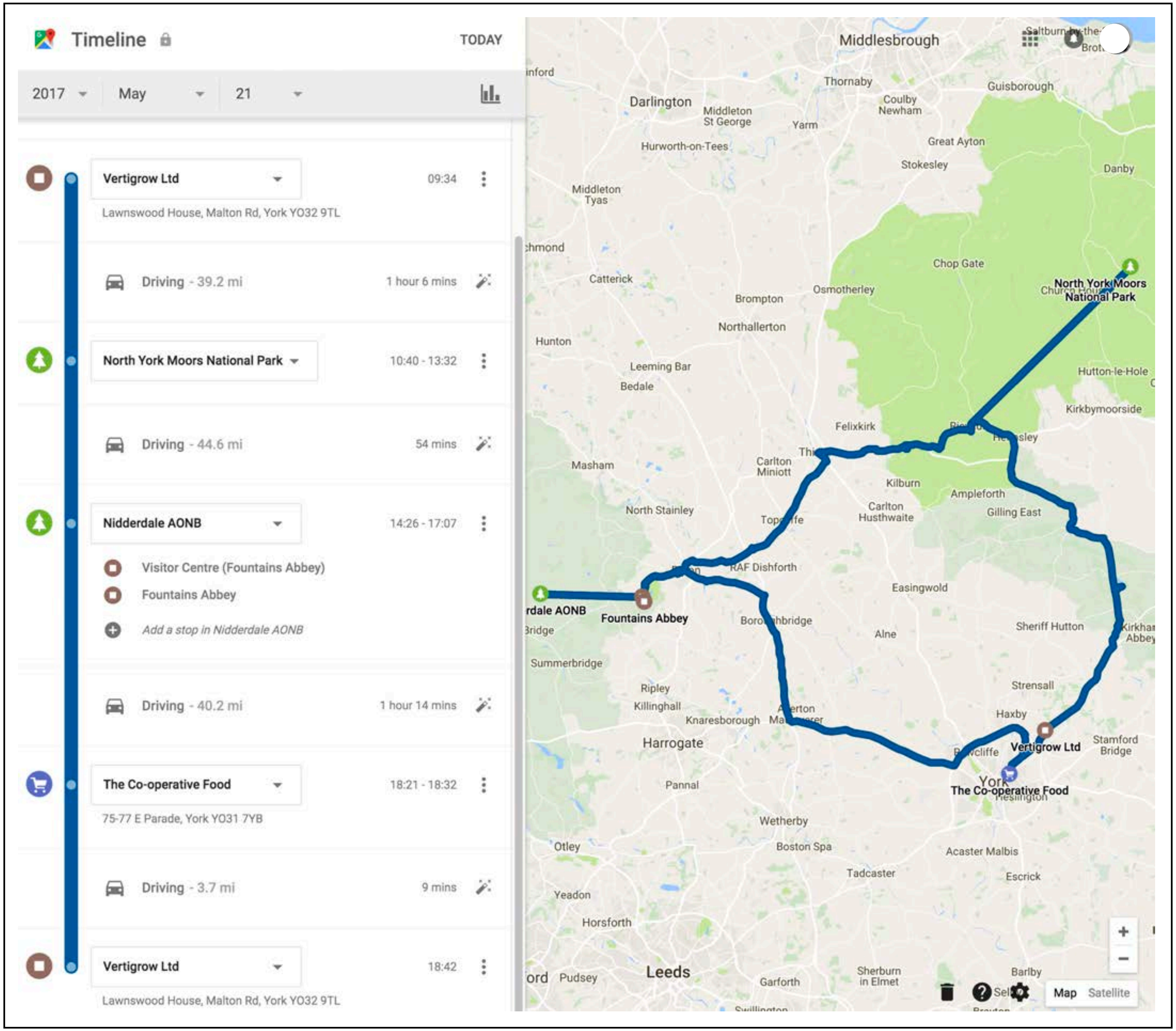
Outdoors (park)

Commute

Indoors (grocer)

Commute

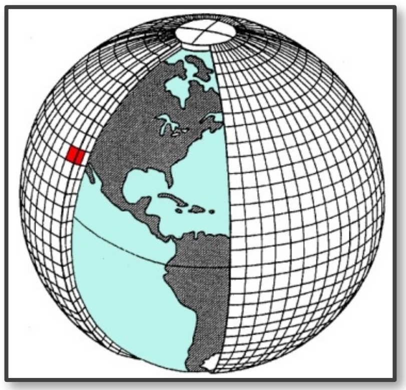
Indoors (hotel)



Test the effect of mobility on personal exposure

Geolocation data from Google Archive of volunteers

- *Sent out data download instructions*
- *Processed data into a usable format*
- *Filtered for spurious locations*



Estimate $PM_{2.5}$ and ozone individuals are exposed to with the GEOS-Chem model using:

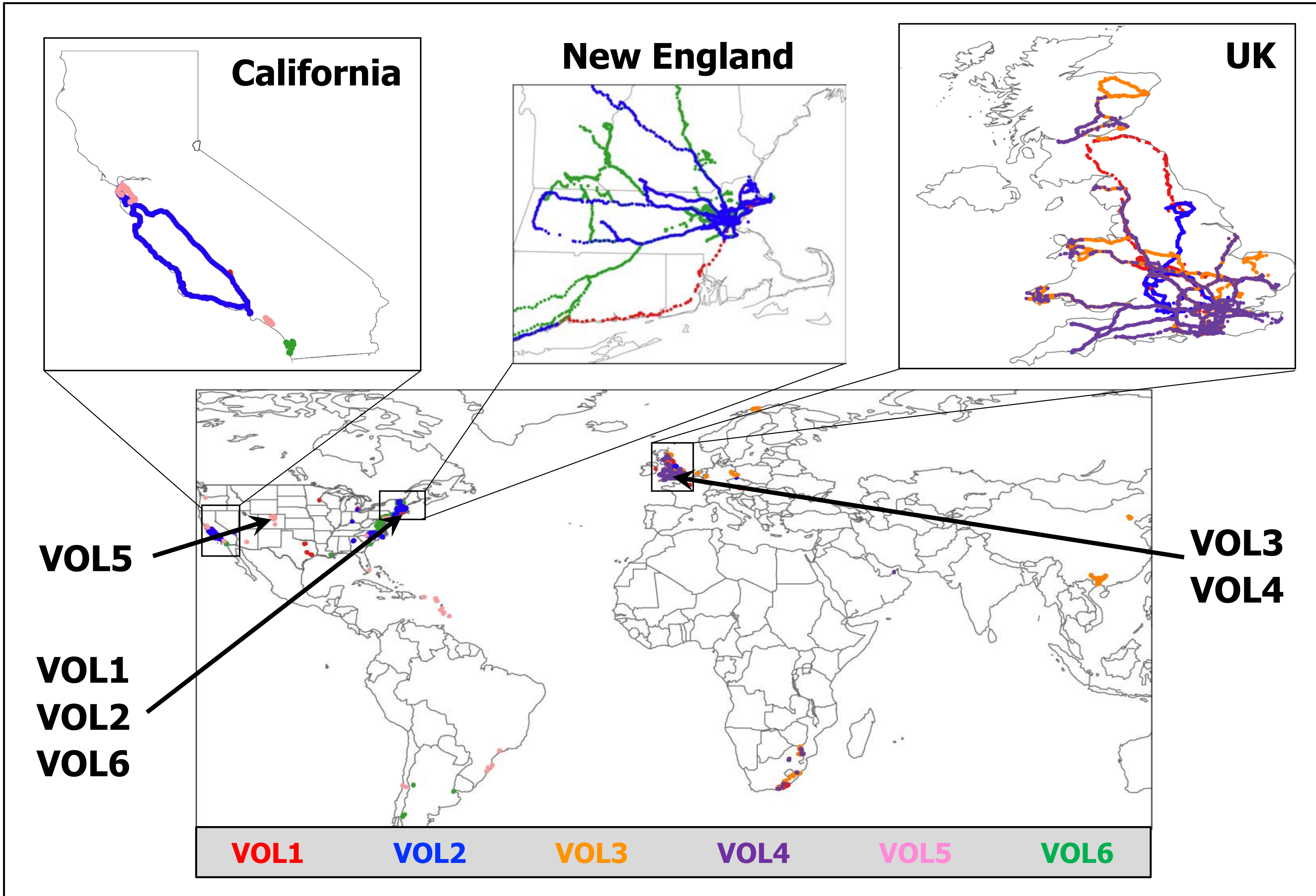
1. *Geolocation data*
2. *Postal address as defined by census data*

Model is at coarse global resolution (**2º × 2.5º**; latitude × longitude)

Most location data available for 2 years (mid-2015 to mid-2017).

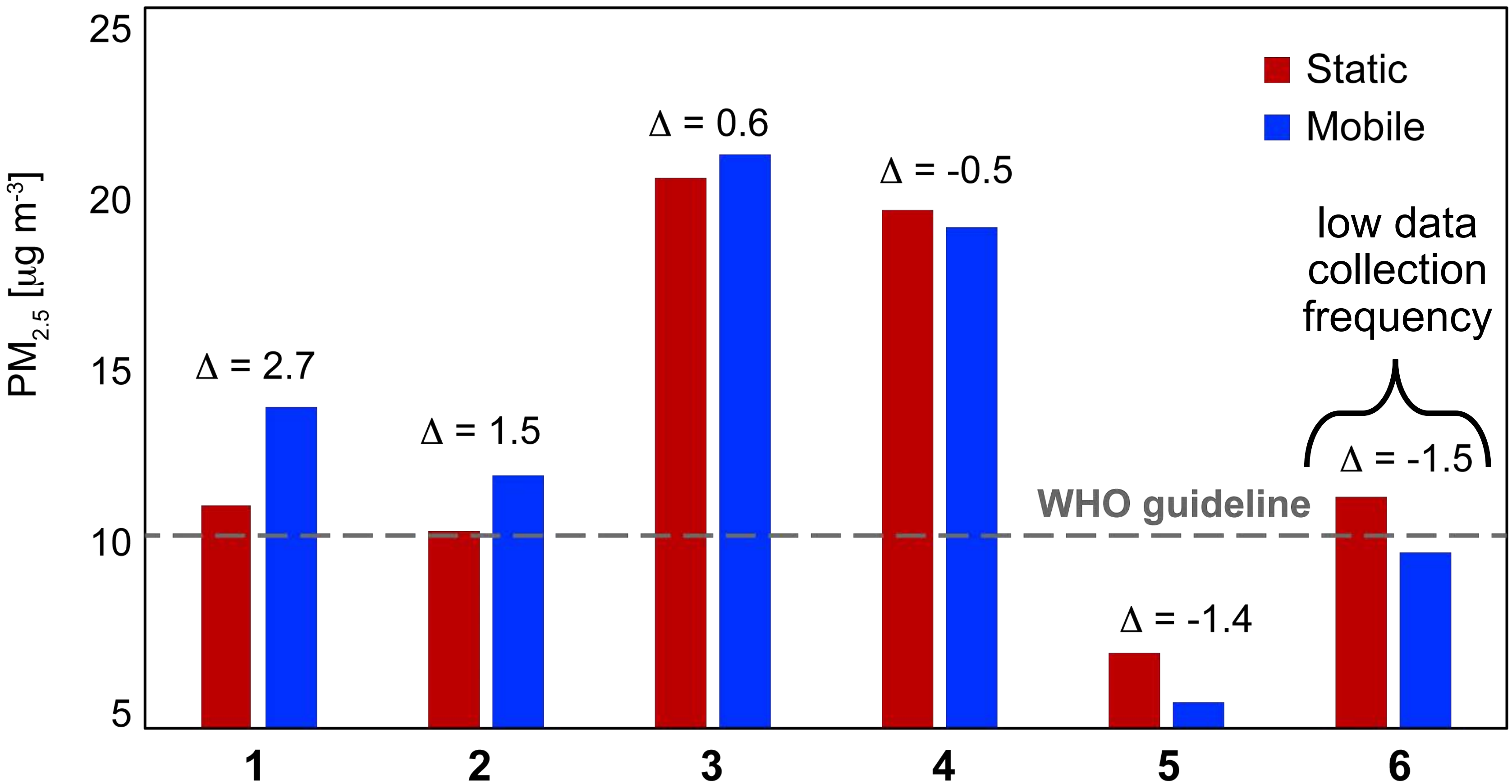
Compare mobile and static surface $PM_{2.5}$ and ozone concentrations

Mobile (coloured points) and static (black arrows) locations of volunteers



Effect of mobility on annual mean $PM_{2.5}$ mass concentrations sampled in GEOS-Chem

Average static and mobile fine particle mass concentrations



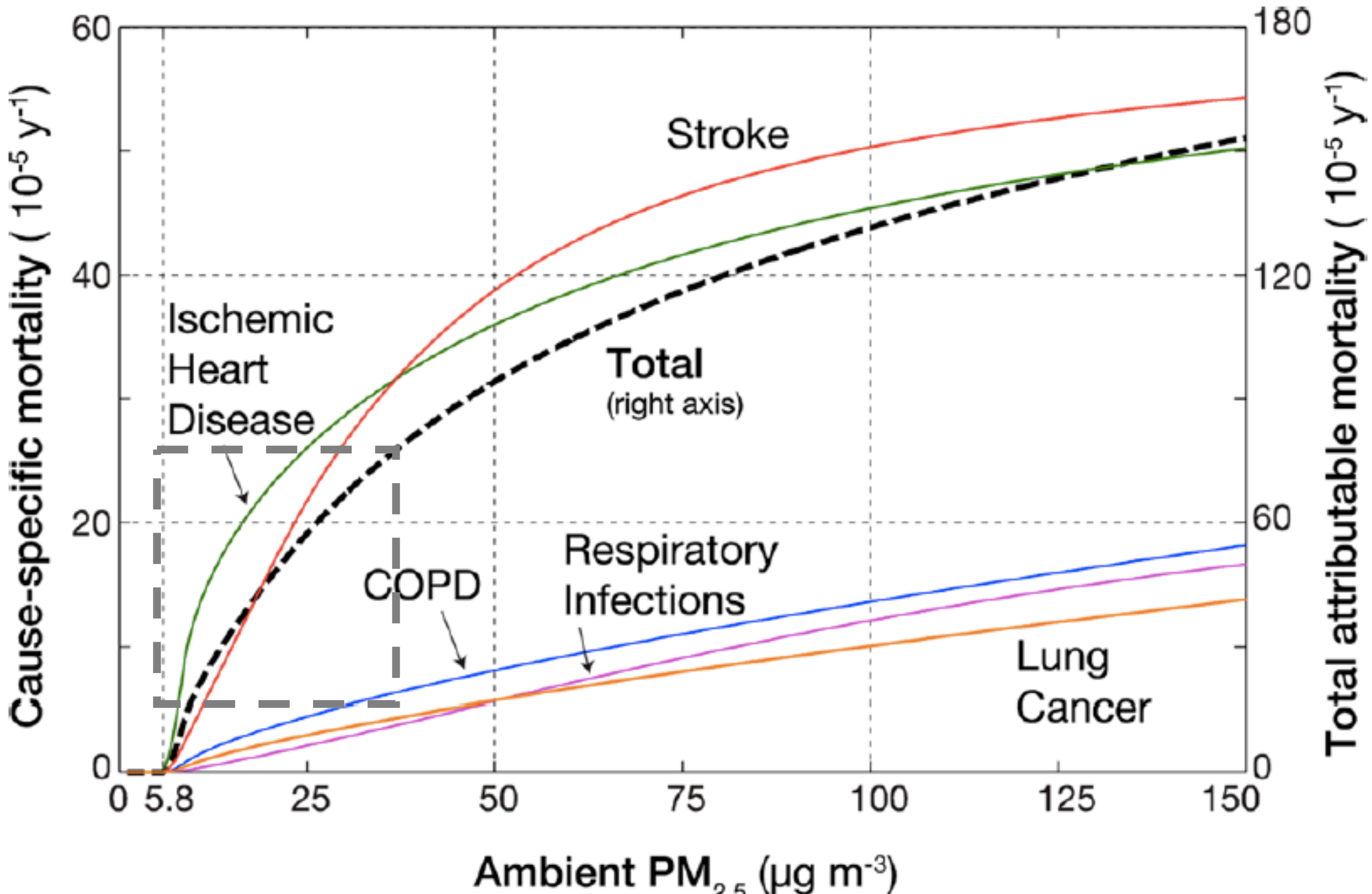
No consistent impact of travel on exposure to $PM_{2.5}$

Volunteers 1 and 2 settled in UK: detrimental to health.

Volunteer 5 travels to central and South America: benefits health

Health risks associated with exposure to $PM_{2.5}$

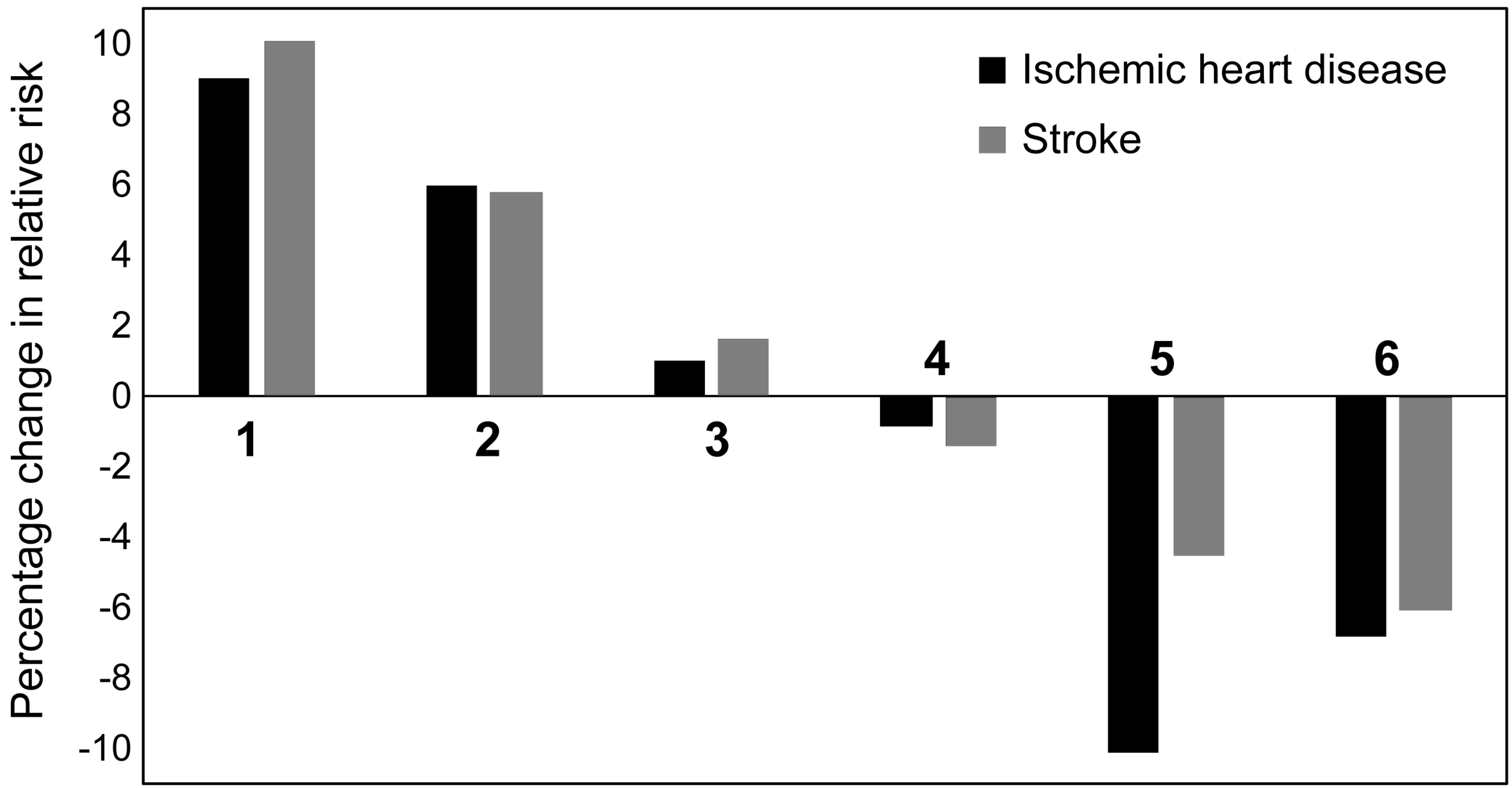
Risk of **ischemic heart disease** and **stroke** very sensitive to small changes in $PM_{2.5}$



[Apte et al., 2015]

Impact of mobility on health

Percentage change in relative risk



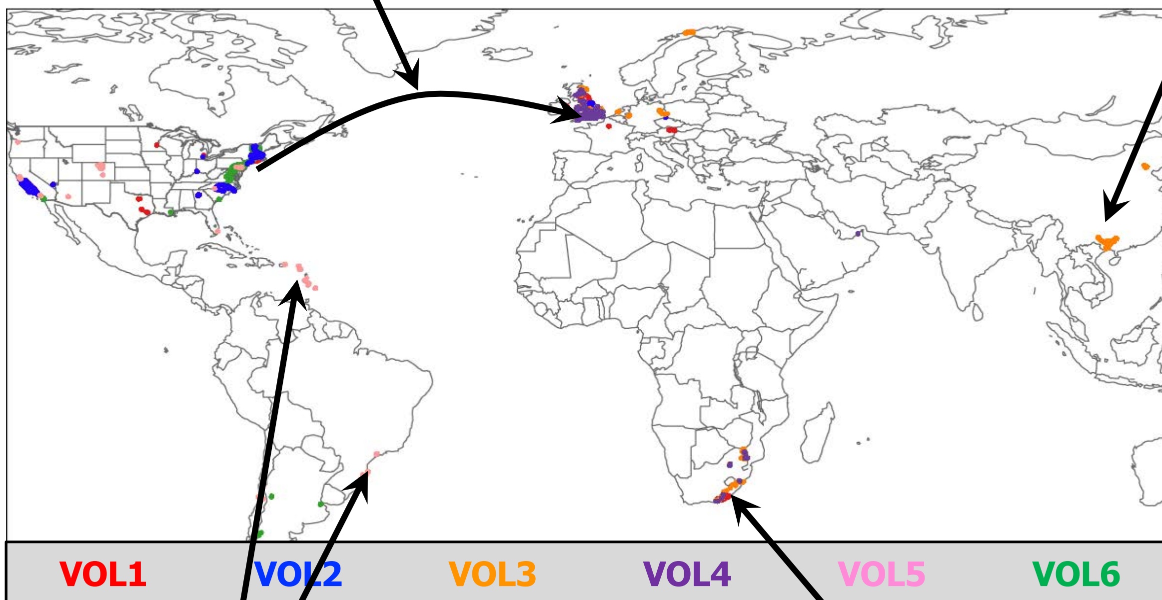
Small changes in $PM_{2.5}$, but large effects on health risks

Geolocation data collection frequency of volunteer 6 too low to be robust

Impact of global travel on exposure

Locating from **US to UK** increases $PM_{2.5}$ exposure by 5-11 $\mu g\ m^{-3}$.

Trip to **China** increases $PM_{2.5}$ exposure by 22 $\mu g\ m^{-3}$.



Frequent trips to central America and South America keeps VOL5 $PM_{2.5}$ exposure well below WHO guideline.

Trip to **South Africa** decreases $PM_{2.5}$ exposure relative to UK/US.

Impact of commuting on exposure

Volunteers 3 and 4 frequently commute to/from London for work

Ozone is 5-7 ppbv lower in London than at home

NO_x is 5 ppbv higher in London than at home

Part of commute is two stops (5-6 min) on the underground

Mean $PM_{2.5}$ concentrations on their line: **131.6 μg m^{-3}** (Rivas et al., 2017)

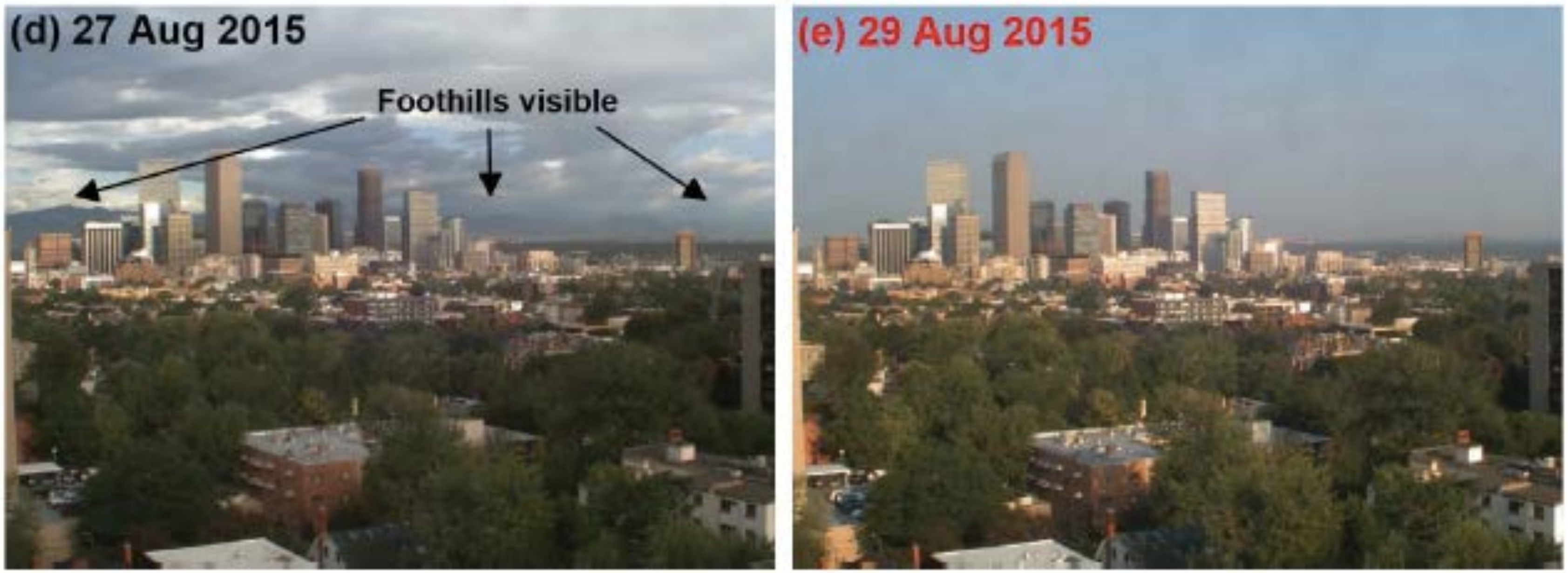
Exposure to $PM_{2.5}$ in London increases by 6-9 μg m^{-3}.

Contributes additional 1 μg m^{-3} to annual mean

UNDERGROUND

Exposure to Pollution Episodes

Unprecedented wildfires in Pacific Northwest in August 2015 degraded air quality in Boulder, CO



[Creamean et al., ACP, 2016]

Replace volunteer 1 GEOS-Chem $PM_{2.5}$ with daily means from surface measurements

Volunteer 1 exposure to $PM_{2.5}$ doubles to 16.9 $\mu g\ m^{-3}$

Increases annual mean $PM_{2.5}$ by 0.4 $\mu g\ m^{-3}$ (1.6% increase in health risk).

Caveats and Challenges using the Data

Requires filtering for spurious locations

Large variability in data collection frequency

Data format (JSON or KML) not ideal for big data analysis

Only 30% of people I approached had this feature turned on (invasive)

Potential applications of Google Location History

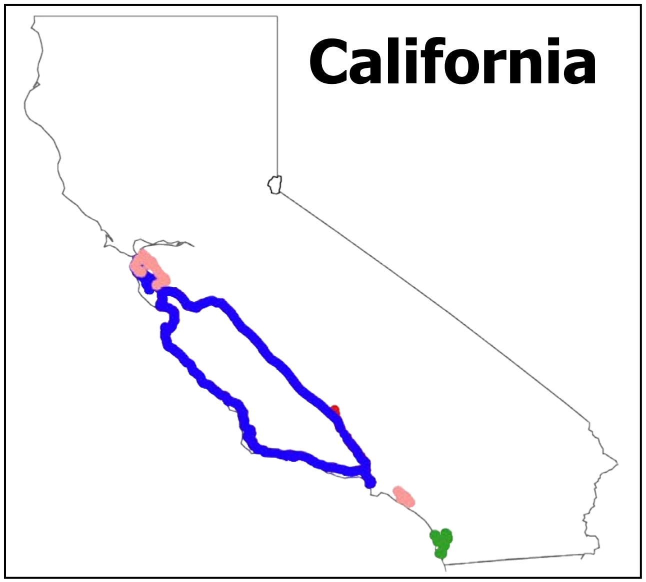
- **Cohort studies**
- Use with **fitness trackers** to estimate inhaled dose
- **Lifestyle decisions:** how behavior impacts health risk
- **Indoor air pollution:** potential to exploit metadata to examine combined effect of indoor and outdoor air pollution on health
- Use with **high-resolution models** (resource intensive)
- Use with dense **surface monitoring** networks
- Future **space-based air quality monitors** in geostationary orbit

Supplementary Slides

Large Variability in Data Collection Frequency

Bin data into 15-minute averages to limiting biasing data toward periods of high collection frequency.

Evaluate using California trip of volunteers 1 and 2



Volunteers 1 and 2 travelled together from Los Angeles to San Francisco and back

Number of data points collected by two volunteers different: 2,400 (volunteer 1), 6,100 (volunteer 2)

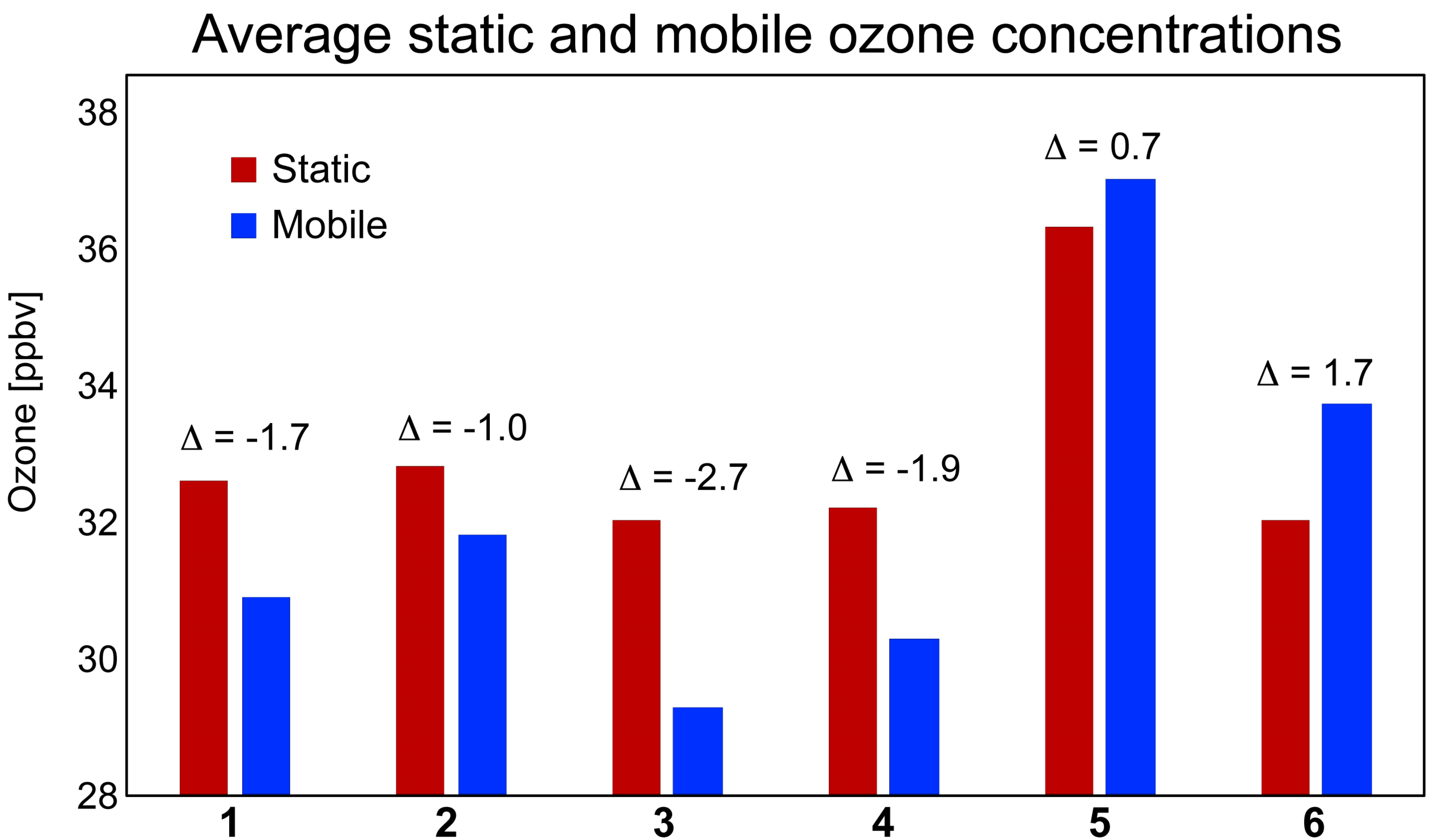
Raw data

Difference between volunteers 1 and 2 is 0.7 $\mu g\ m^{-3}$ ($PM_{2.5}$) and 5.6 ppbv (ozone)

15-minute bins

Difference between volunteers 1 and 2 is 1.0 $\mu g\ m^{-3}$ ($PM_{2.5}$); 3.5 ppbv (ozone)

Effect of mobility on annual mean ozone concentrations sampled in GEOS-Chem



Move to UK and commuting to/from London decreases ozone exposure (high concentrations of NO_x in London and UK cities in general)