

Advances in Modeling of Human Exposure to Air Pollution

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Background

- Most people spend over 80% of their time in enclosed microenvironments (home, bus, school, etc.)
- Most exposure to ambient pollution takes place in enclosed microenvironments
- Hence, actual exposure is determined by targetable factors including emissions, dispersion, built environment, infiltration, and activity patterns
- There are more ways to manage exposure than just managing emissions

What is Exposure?

- Frequency, intensity, and duration of **contact** of a **pollutant (p)** with the **outer boundary of the body**
- Microenvironmental concentrations $C_{p,m}$ in the breathing zone must be quantified
 - Ambient concentration for outdoors (spatial and temporal variability)
 - Depends on infiltration of ambient pollution into enclosed microenvironments
- Individual time activity patterns must be quantified
- **Stochastic population-based exposure simulation** is based on quantifying **individual (i)** contact with **pollutant (p)** in each **microenvironment (m)**

$$E_{i,p} = \sum_m C_{p,m} \Delta t_{i,m}$$

- Simulation is done for a particular geographic area, population of interest, averaging time (e.g., hourly, daily) and time period

How is Exposure Quantified?

- **Point of Contact Method** - Measurements with personal monitoring devices
- **Scenario Evaluation Method** - Measurements with environmental monitoring at selected sites
- **Reconstruction of Dose Method** - Measurement of biomarkers in individuals (e.g., metabolite, excreted materials)

Conceptual Source-Exposure Model

Source-to-Exposure Continuum

- Emissions, Q
- Transport and Fate (Concentration), C
- Exposure, E

$$E = Q \left(\frac{C}{Q} \right) \left(\frac{E}{C} \right)$$

Emissions Air Quality Exposure

Opportunities for Exposure Assessment

National Research Council (2012): “*Exposure Science in the 21st Century: A Vision and Strategy*”

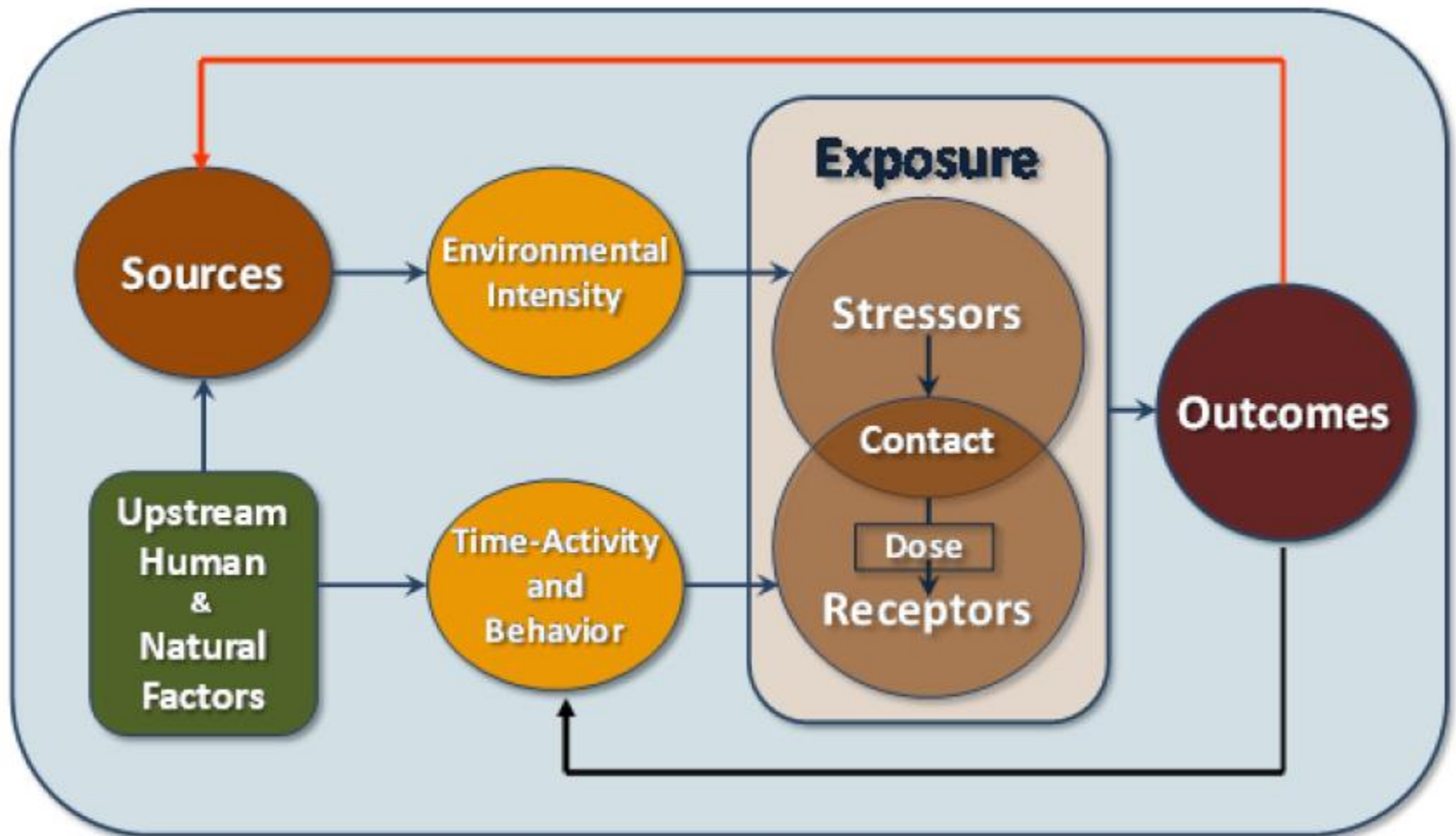
- Exposure science is relatively new compared to other disciplines.
- Key Challenges, Barriers, and Opportunities
 - Human Activity Data
 - Microenvironmental Air Quality Data
 - Time-Activity Exposure Assessment
 - Exposure Management



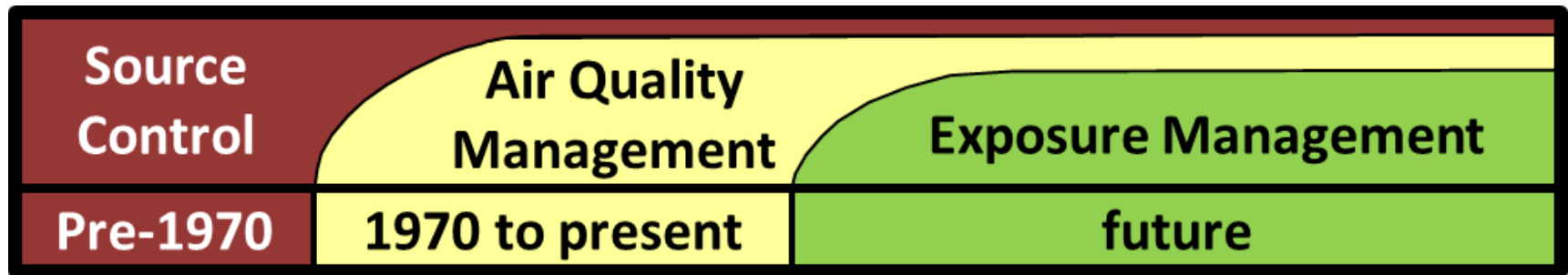
Examples of Key Questions to be Answered by the Exposure-based Methodology

- What are the **cross-sectional differences** in activities among individuals?
- What are the **longitudinal activity patterns**?
- What is the **variability** in exposure concentration between microenvironments?
- **How sensitive are exposures** to time activity patterns and microenvironmental concentrations?
- **Which activities and microenvironments** contribute to the **highest exposures** among populations of interest?
- **Which sources** of variability in exposures are **controllable**, to enable **targeting** of effective management strategies?

Exposure Science in the 21st Century: National Research Council



Moving Toward a New Paradigm



- **Source control:** ineffective at improving air quality (e.g., ozone, particulate matter)
- **Air quality management:** ineffective at preventing high end exposures to sensitive populations
- **Exposure management:** there are more ways to manage exposure beyond managing air quality

Variability and Uncertainty

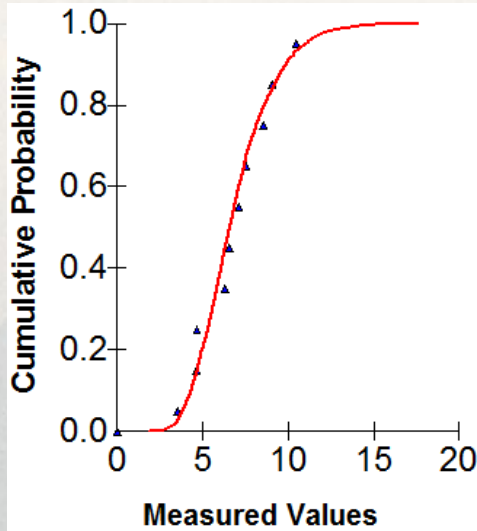
Variability

- Variability arises from true heterogeneity across people, places or time
- Affects the precision of exposure estimates and the degree to which they can be generalized.
- Types of variability include: spatial, temporal, intra- and inter-individual
- Controllable sources of variability are targets for exposure management

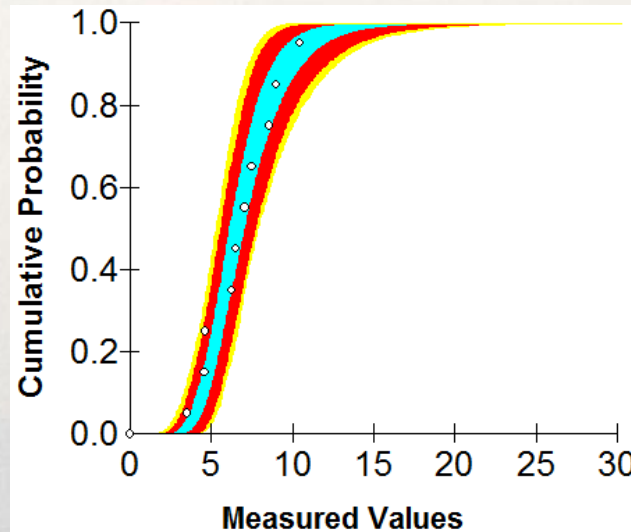
Uncertainty

- Uncertainty represents a lack of knowledge about factors affecting exposure or risk
- Principal types of uncertainty, include: scenario, parameter, and model
- Uncertainty can be reduced via targeted field studies and improved inference methods (e.g., models) to better quantify inter-individual variability.

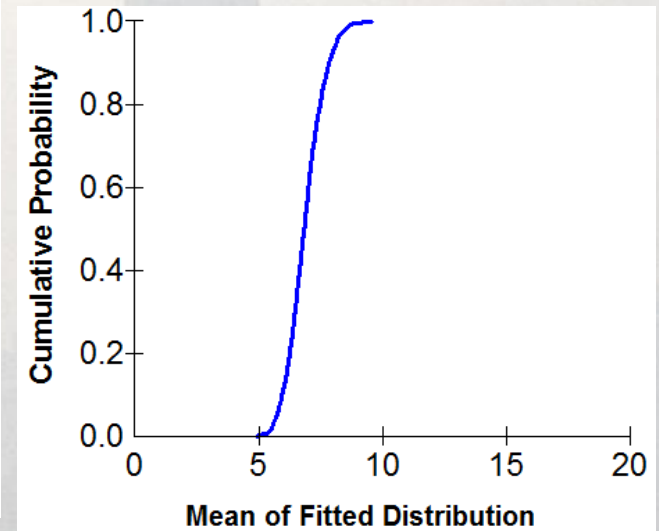
Quantifying Variability and Uncertainty from Measured Data: Example



(a) Fitted Distribution



(b) Bootstrap Simulation



(c) Uncertainty in Mean Value

Despite small sample size, uncertainty in mean is only approximately $\pm 20\%$ and uncertainty in upper tail is quantifiable.

Frey, H.C., and D.E. Burmaster, "Methods for Characterizing Variability and Uncertainty: Comparison of Bootstrap Simulation and Likelihood-Based Approaches," Risk Analysis, 19(1):109-130 (February 1999).

Frey, H.C., J. Zheng, Y. Zhao, S. Li, and Y. Zhu, Technical Documentation of the AuvTool Software for Analysis of Variability and Uncertainty, Prepared by North Carolina State University for the Office of Research and Development, U.S. Environmental Protection Agency, Research Triangle Park, NC. February 2002

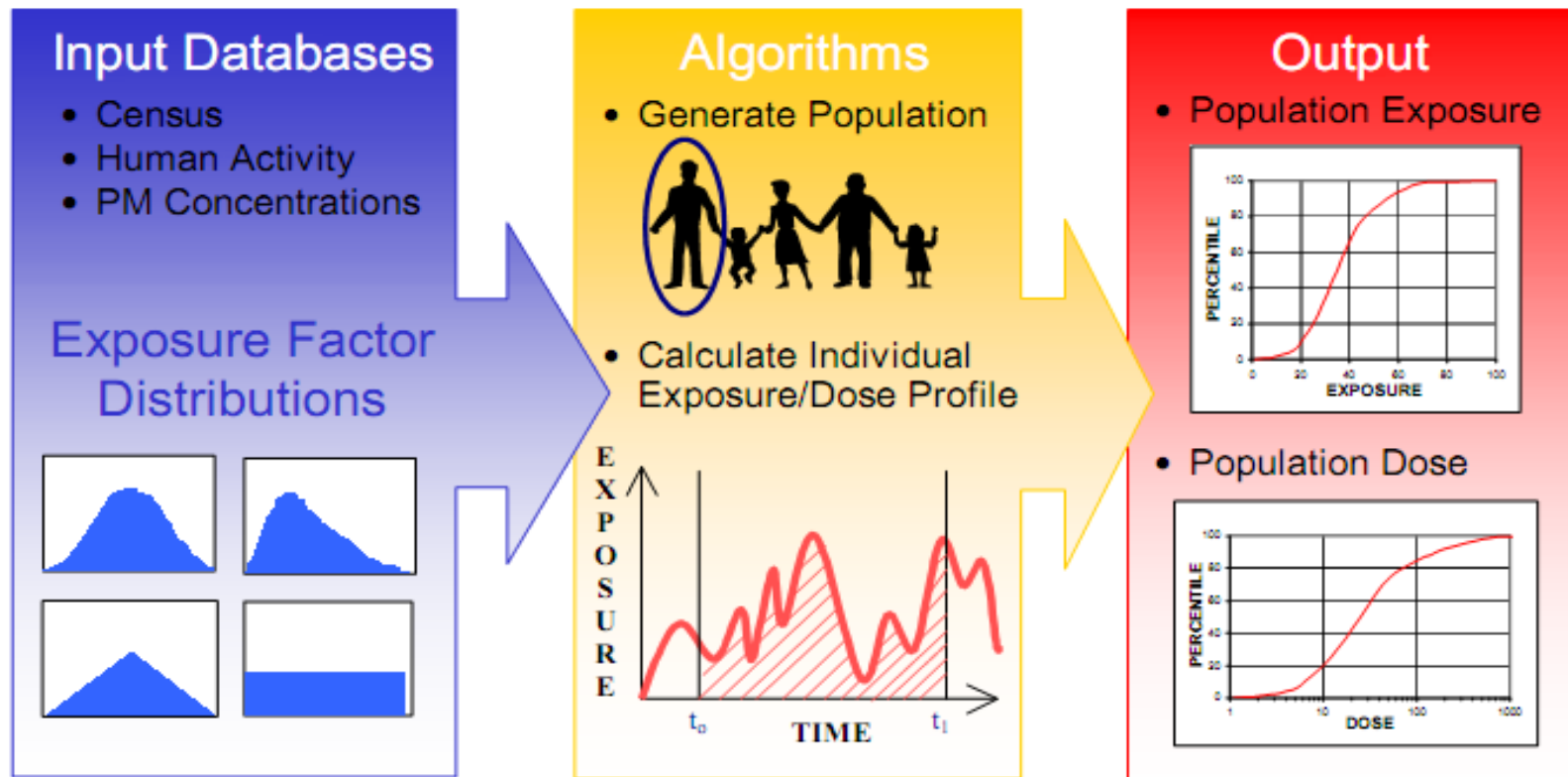
Recent Advances in Exposure Assessment Modeling

- Development of human diary databases – e.g., Consolidated Human Activity Database (CHAD) in the U.S.
- Measurement of selected microenvironments in U.S., Europe
- Development of stochastic population-based simulation models, such as
 - Air Pollution Exposure (APEX) model
 - Stochastic Human Exposure and Dose Simulation (SHEDS) model
- These models have the following key input:
 - Air quality data
 - CHAD
 - Census (demographic) data
 - Microenvironmental concentrations

Stochastic Population-Based Exposure Modeling

- State-of-the-art technique
- Developed and used by U.S. EPA to support revisions of National Ambient Air Quality Standards for criteria air pollutants
 - Carbon Monoxide (2010)
 - Lead (2007 and 2013)
 - Nitrogen Dioxide (2010, and current review cycle)
 - Ozone (2008, and current review cycle)
 - Sulfur dioxide (2009, and current review cycle)
 - PM (expected in upcoming review cycle)
- However, not currently used for ***exposure management***

Modeling Approach: Stochastic Human Exposure and Dose Simulation model for PM_{2.5} (SHEDS-PM)



SHEDS-PM Model Structure

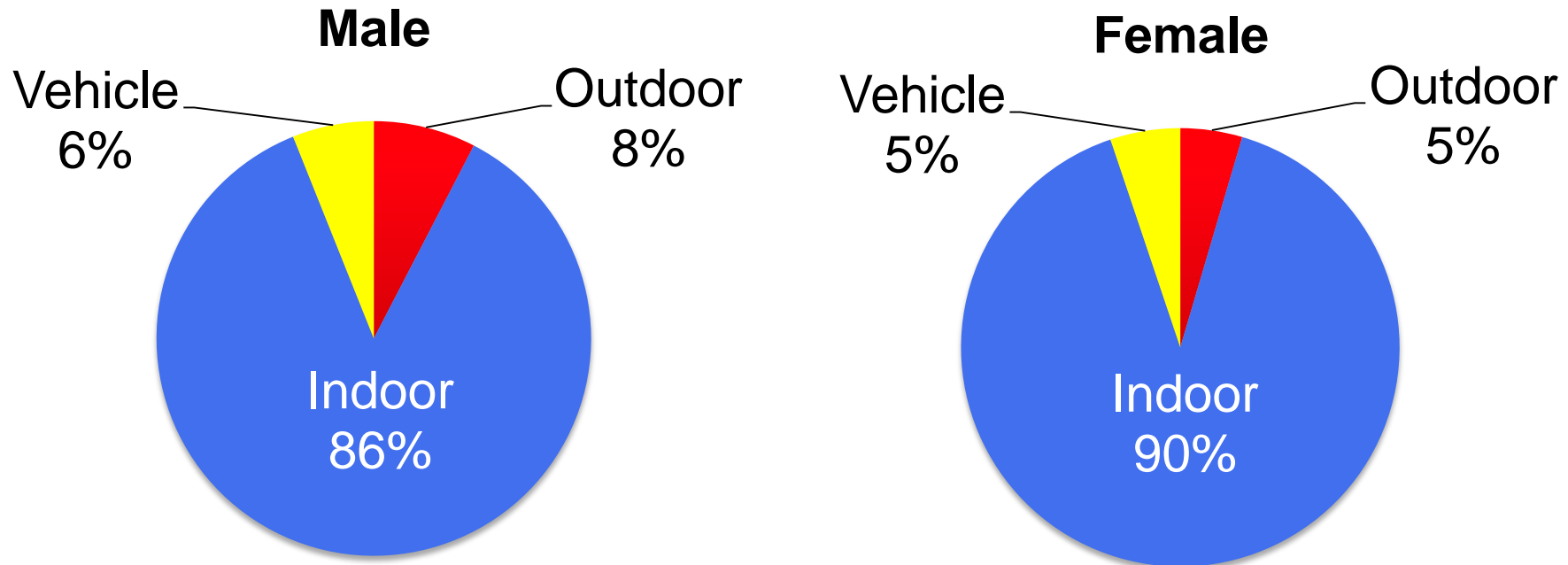
Source: Burke, J.M.; Vedamtham, R. *Stochastic Human Exposure and Dose Simulation for Particulate Matter (SHED-PM) Version 3.5 User Guide*; US Environmental Protection Agency: Research Triangle Park, NC, 2009.

Study Design

Simulation	
Sample Size	Approximately 50,000 individuals
Age Groups	≥ 65 years old
Areas	Bronx, New York, and Queens County in New York City
Years	2002 – 2006
Simulation Type	Longitudinal
Air Quality Data	Daily 12 km by 12 km grid cells concentrations from EPA Community Multiscale Air Quality (CMAQ) System
Demographics	Year 2000 US Census
Activity Patterns	Consolidated Human Activity Database (CHAD)

New York city example from Jiao and Frey (2013)
Using a stochastic population based exposure model

Distribution of Daily Activity Patterns



- Source: Consolidated Human Activity Database (CHAD) (McCurdy et al., 2005)
- **Outdoor** includes street, parking lot, gas station, park, playgrounds, pool, farm, and all other outdoor microenvironments
- **Indoor** includes home, office, school, store, bar, restaurant, and all other indoor microenvironments
- **In vehicle** includes travel by car, truck, motorcycle, bus, train, subway, airplane, boat, walking, bicycle, and waiting for travel either indoor or outdoor.

Indoor Home Ambient PM_{2.5} Concentration

$$C_r = \left(\frac{P \cdot ACH}{ACH + k} \right) C_a$$

Where

C_r = indoor residential ambient PM_{2.5} concentration ($\mu\text{g}/\text{m}^3$)

C_a = ambient outdoor PM_{2.5} concentration ($\mu\text{g}/\text{m}^3$)

P = penetration factor (unitless)

ACH = air exchange rate (h^{-1})

k = deposition factor (h^{-1})

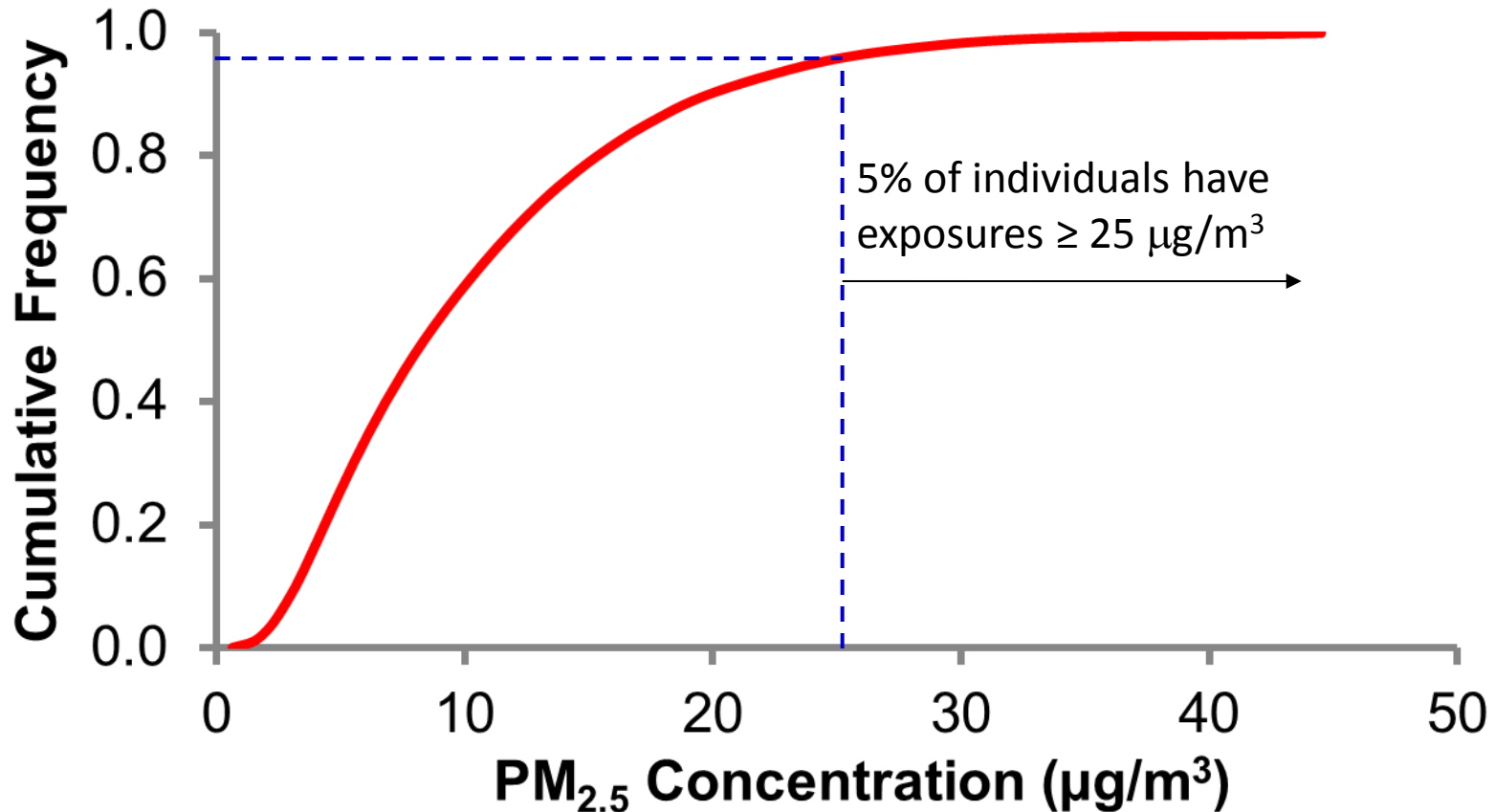
Indoor Home Microenvironment Input Parameters

Parameter	Distribution Type ^a	Temperature	Value ^b
Penetration (P)	Triangular	ALL	Min=0.70, Mode=0.78, Max=1.0
Deposition (k)	Normal	ALL	$\mu=0.40 \text{ h}^{-1}$, $\sigma=0.10 \text{ h}^{-1}$
Air Exchange Rate (ACH)	Lognormal	Cold (<65 °F)	$\mu_g=0.78 \text{ h}^{-1}$, $\sigma_g=1.94 \text{ h}^{-1}$
		Warm ($\geq 65 \text{ °F}$)	$\mu_g=1.44 \text{ h}^{-1}$, $\sigma_g=2.14 \text{ h}^{-1}$

^a. Triangular distribution parameters are the minimum, mode, and maximum; normal distribution parameters are the mean μ and standard deviation σ ; lognormal distribution parameters are the geometric mean μ_g and geometric standard deviation σ_g .

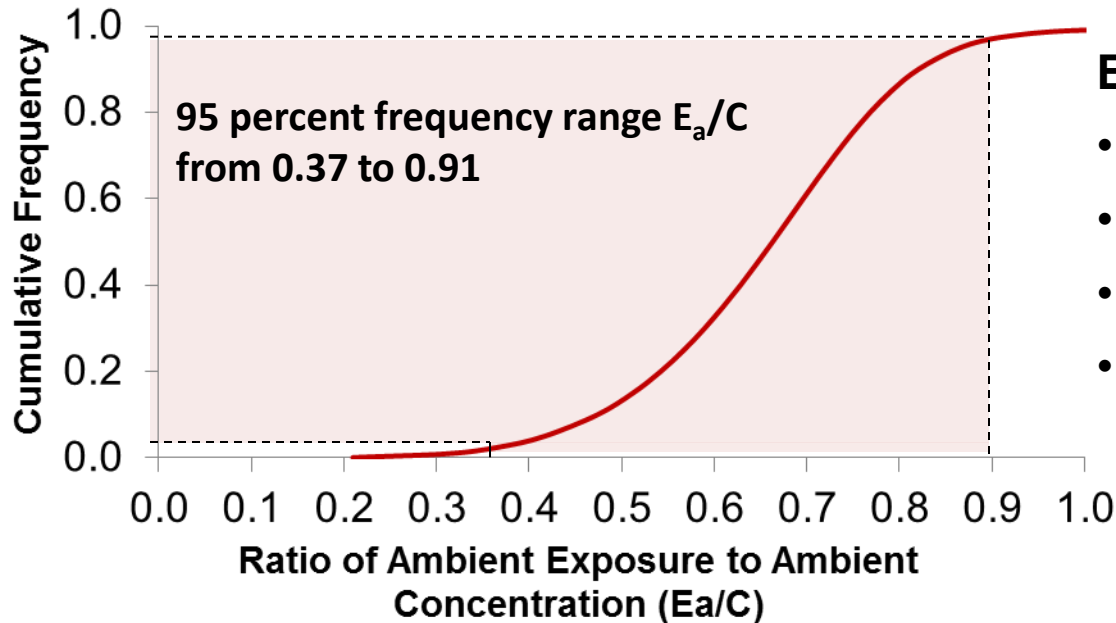
^b. Sources: P, k: Weisel et al. (2005), Özkaynak et al. (1996); ACH: Jones et al. (2012)

Example: Cumulative Distribution Function (CDF) of Inter-individual Variability in Daily Average Exposure (E_a)



New York city example from Jiao and Frey (2013)
Using a stochastic population based exposure model

Factors Affecting Inter-Individual Variability in $PM_{2.5}$ Exposure



E_a/C ratio is correlated with

- Residential air exchange rate
- Time spent at home
- Time spent in vehicle
- Time spent outdoors

- The daily E_a/C ratio is not the same for everyone, but differs widely among individuals by a factor of 2.5 over a 95% frequency range.
- NYC example from Jiao and Frey (2013), presented at Society for Risk Analysis annual meeting, using a stochastic population-based exposure model

Inter-Annual Variation in Daily Averages

Year	C		E_a		E_a/C	
	Mean ($\mu\text{g}/\text{m}^3$)	CV	Mean ($\mu\text{g}/\text{m}^3$)	CV	Mean	CV
2002	15.6	0.65	10.2	0.69	0.66	0.22
2003	16.2	0.68	10.4	0.72	0.65	0.22
2004	14.7	0.69	9.5	0.72	0.66	0.22
2005	14.5	0.69	9.3	0.72	0.65	0.23
2006	14.7	0.72	9.6	0.75	0.66	0.22

- Difference between the highest (2003) and lowest (2005) estimated annual average CMAQ estimates of C was 11.7%.
- For FSM, the difference was 16.4%.

Inter-Annual Variation in Daily Averages

Year	C		E _a		E _a /C	
	Mean (μg/m ³)	CV	Mean (μg/m ³)	CV	Mean	CV
2002	15.6	0.65	10.2	0.69	0.66	0.22
2003	16.2	0.68	10.4	0.72	0.65	0.22
2004	14.7	0.69	9.5	0.72	0.66	0.22
2005	14.5	0.69	9.3	0.72	0.65	0.23
2006	14.7	0.72	9.6	0.75	0.66	0.22

- Difference between the highest and lowest estimated annual average of E_a/C was 1.5%.

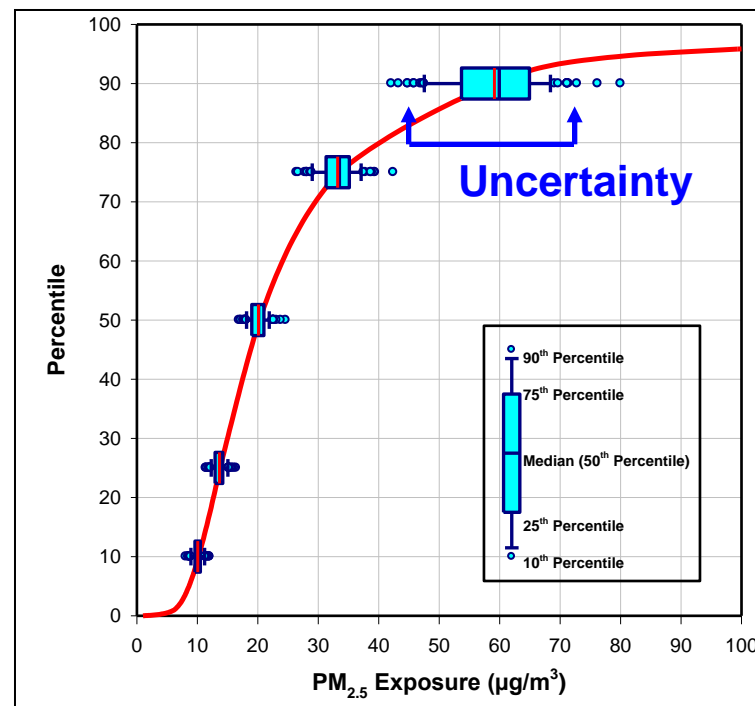
Seasonal Variability by County in a Single Year, 2002

County	Season	C, $\mu\text{g}/\text{m}^3$		E_a , $\mu\text{g}/\text{m}^3$		E_a/C	
		Mean	CV	Mean	CV	Mean	CV
Bronx	Winter	17.5	0.61	11.0	0.66	0.63	0.22
	Summer	12.3	0.61	8.5	0.64	0.70	0.20
New York	Winter	23.8	0.56	15.0	0.61	0.63	0.22
	Summer	16.7	0.58	11.5	0.61	0.69	0.19
Queens	Winter	19.1	0.54	12.1	0.59	0.63	0.22
	Summer	13.2	0.58	9.2	0.61	0.70	0.19

- E_a/C differed by approximately 10% between seasons.
- Other than C, seasonal difference in exposure was mainly related to differences in ACH.

Variability and Uncertainty in Exposure Estimates: An Example

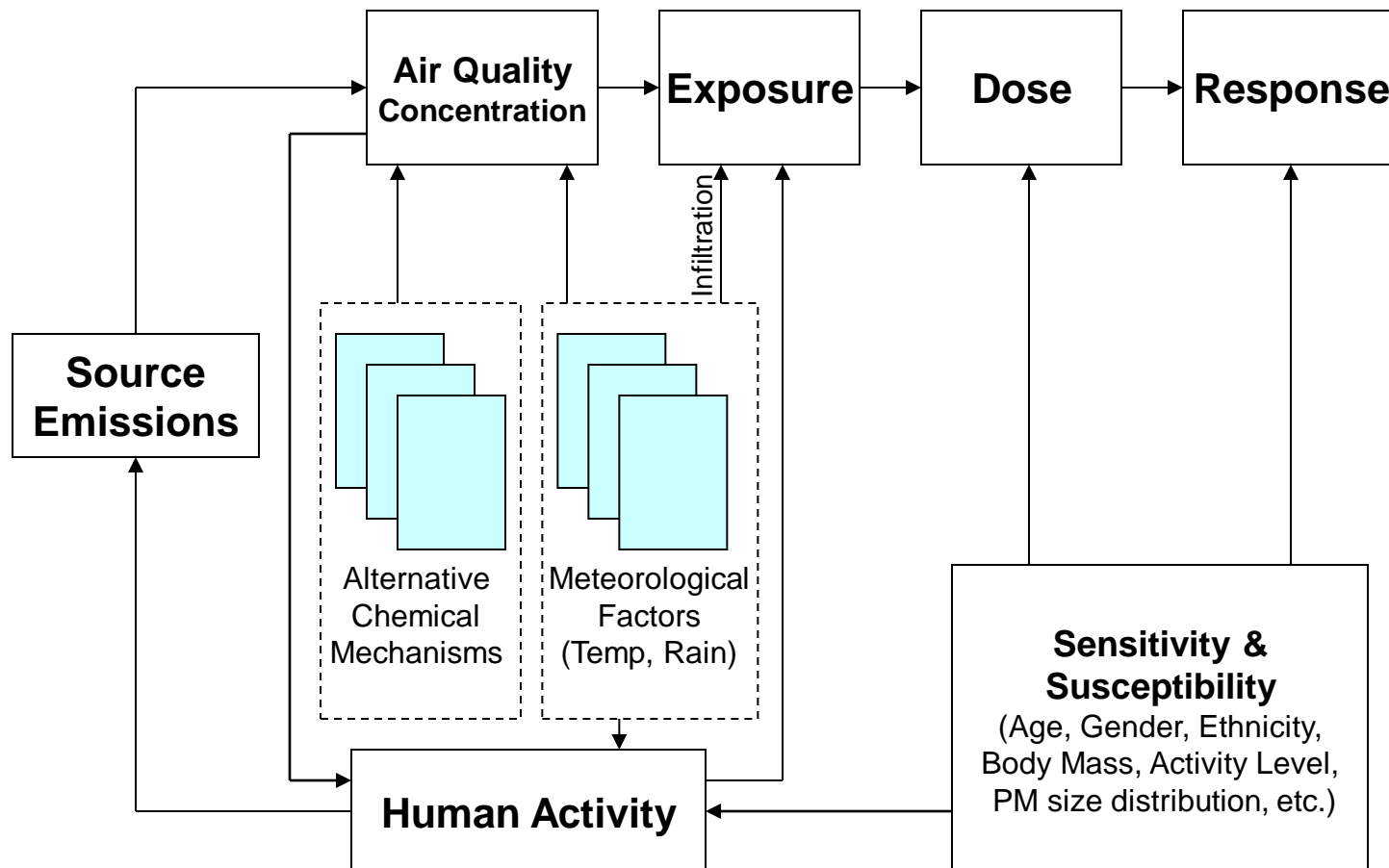
Total PM_{2.5} Exposure



SHEDS-PM Philadelphia PM_{2.5} Case Study

Source: J. Burke, U.S. EPA

Linkages in the Source-to-Response Continuum



Current and Future Directions for Exposure Assessment

Advances in tools and technologies

- sensor systems
- analytic methods
- computational tools
- and others

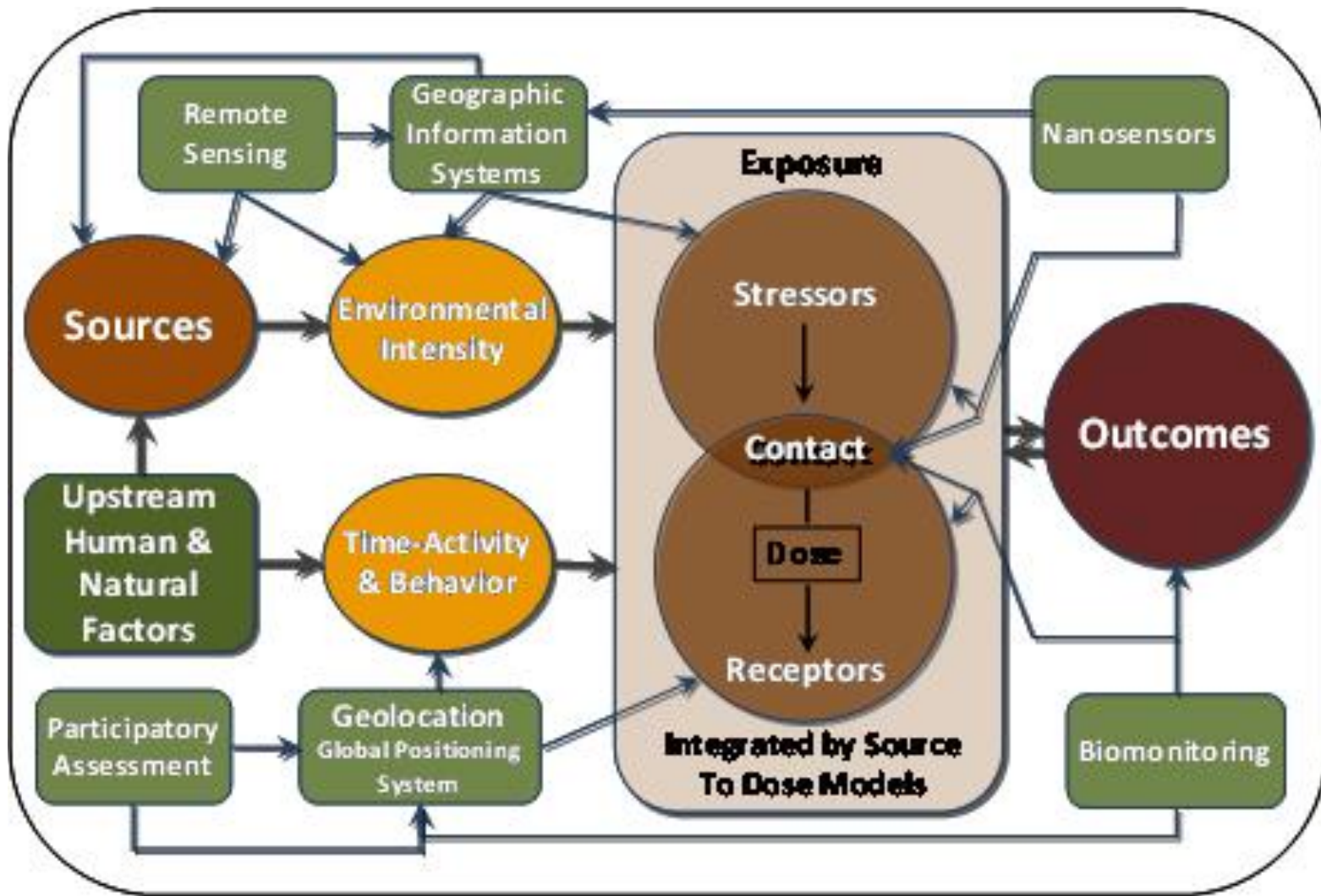
Exposure Assessment Vision

- Development of an *integrated systems approach* to exposure science that is more fully coordinated with other fields of environmental health
- Better address scientific, regulatory, and societal challenges
- Provide exposure information to a larger population
- Embrace both human health and ecosystem protection
- Privacy?

Examples of Emerging Opportunities

- Numerous state-of-the-art methods to measure
 - Microenvironmental concentrations
 - Personal exposures
 - Biomarkers
- Developments in geographic information science and technologies
 - Satellites, remote sensing
 - Improved information on physical activity locations of humans and other species obtained with global positioning systems
 - Geolocation technologies combined with cellular telephone technologies.
- Integrated sensing systems could facilitate individual-level exposure assessments in large populations of humans or other species

Data Sources to Support Exposure Assessment



Addressing Exposure Error in Epidemiologic Studies

- Multi-city and multi-season epidemiologic studies typically find variability in concentration-response functions
- Such variation may be due to variations in activity patterns, air exchange rate, and other exposure factors
- Exposure rather than ambient concentration could increase the statistical power of epidemiologic models

Examples:

Chang, H.H., M. Fuentes, and H. C. Frey, "Time Series Analysis of Personal Exposure to Ambient Air Pollution and Mortality Using an Exposure Simulator," *Journal of Exposure Science and Environmental Epidemiology*, 22, 483-488 (2012)

Mannshardt, E., K. Sucic, W. Jiao, F. Dominici, H.C. Frey, B. Reich, and M. Fuentes (2013), Comparing Exposure Metrics for the Effects of Fine Particulate Matter on Emergency Hospital Admissions, *Journal of Exposure Science and Environmental Epidemiology*, 23:627-636

Portable Instruments

- Portable instruments have been commercially available for a decade or more to enable measurement of microenvironmental concentrations for *some* pollutants

Example of Measurement of Microenvironmental Exposure Concentration: Selected Transportation Modes



- Transit Bus



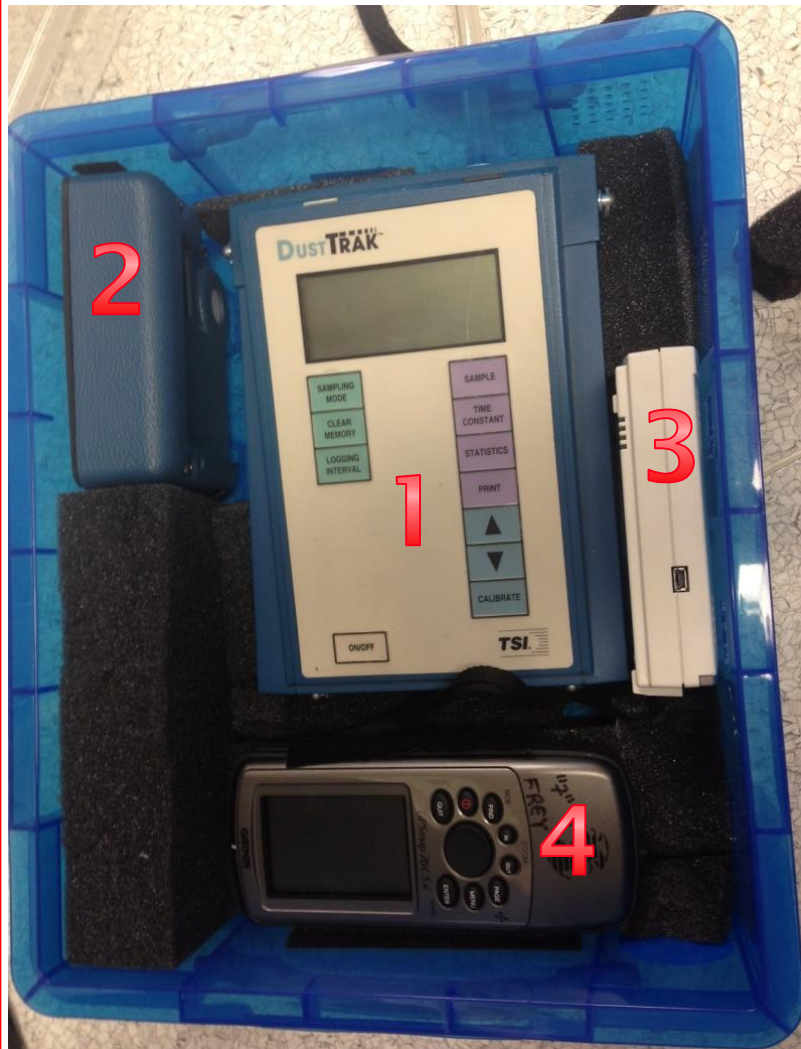
- Personal cars



- Pedestrian

Jiao, W., and H.C. Frey, "Comparison of Fine Particulate Matter and Carbon Monoxide Exposure Concentrations for Selected Transportation Modes," *Transportation Research Record*, accepted 2/10/14

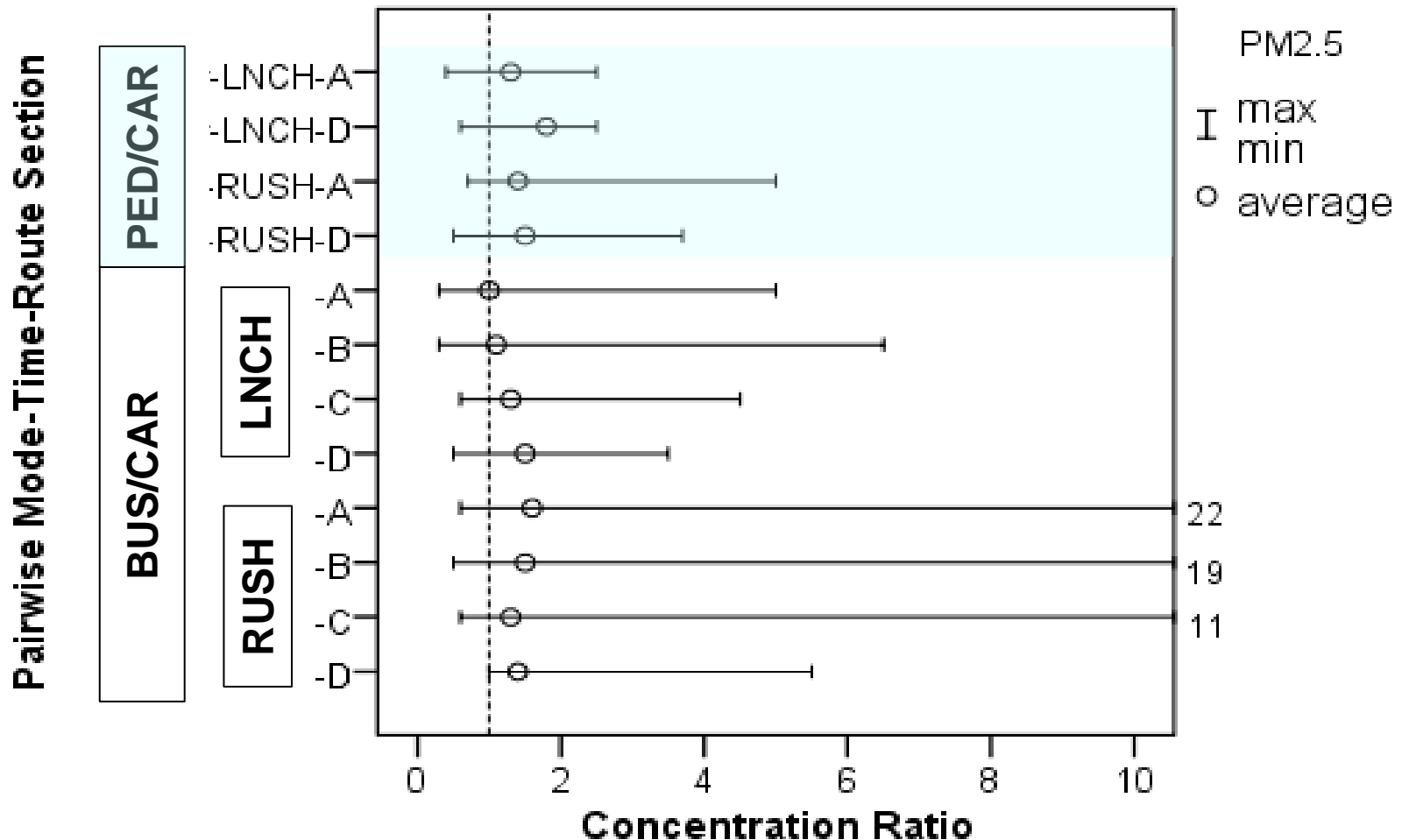
Portable Instruments



- 1) DustTrak 8520 PM monitor
- 2) Langan T15n CO measurer
- 3) HOBO U14 T/RH logger
- 4) Garmin 76CSx GPS
- 5) UNI-T Anemometer



Distributions of PM_{2.5} Concentration Ratio by Pairwise Transportation Modes, Time of Day, and Route Section



Findings from the Example Transportation Microenvironment Study

- As expected, in-car PM_{2.5} concentrations are low with windows closed and use of recirculated air
- High bus PM_{2.5} exposures related to bus stops and air exchange, and possibly “self-pollution”
- High car CO exposures related to proximity to onroad emission sources and possibly “self-pollution”
- Exposures vary by time of day and to a lesser extent by location along the study route, mostly likely attributable to traffic or traffic control.

Development of Small Low-Cost Sensors

- There is a lot of interest in the possibility of small low-cost sensors
- Citizen-scientist
- Ubiquitous monitoring
- Precision, accuracy, reliability, comparability
- Appropriate use of instruments and interpretation of data

Some Considerations in Defining an Exposure Assessment

- Which chemicals?
- What end-points (health effects)?
- Exposure pathways? (how does a particular route arise?)
- Exposure Events? (time of contact)
- Exposure Route? (inhalation, ingestion, dermal)
- Averaging time?
- Geographic extent?
- Exposed population?
- Susceptible subgroups?
- Activity patterns?
- Transport and Fate?
- Data quality objectives?

Conclusions

- Exposure Science is Developing in Several Areas:
 - Measurement of activity
 - Measurement of microenvironmental concentration
 - Modeling methods and tools
- Exposure assessment has become accepted as an integral part of reviewing and revising the U.S. NAAQS
- However, there is an opportunity to shift from air quality management to a broader approach based on exposure management
- Emerging technologies and techniques enable development of exposure assessments based on site-specific data