

Spatial Variability in Pollutants: Implications for Exposure Assessment

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ABSTRACT

Measurement studies of air pollutants in populated areas have demonstrated that ambient air concentrations across the community can range from being relatively uniform to being highly variable in space and time. People, too, are variable – moving across the community throughout the day and participating in various activities that affect their actual exposures. The resulting exposure profiles are a function of temporally- and spatially-varying concentrations and activities. The National Exposure Research Laboratory and others have undertaken a number of studies to assess that variability in time and space for a variety of pollutants, source-related emissions, and human activities.

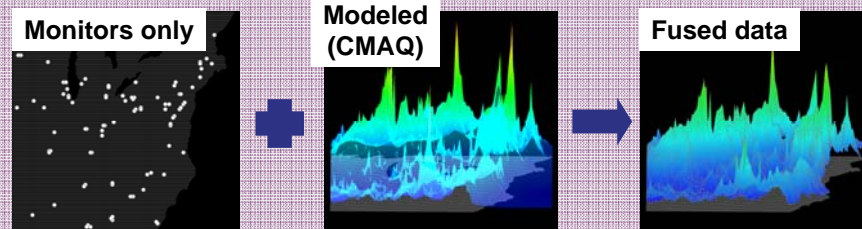
Statistical analyses and modeling have been used to assess the variability in exposure metrics and to relate those metrics to outcomes in complex systems. The impact of that variability on the selection of exposure metric and exposure classification approach (from simple metrics and statistical associations; to statistical interpolation that fuses observational data and modeling results, to cohort estimates of varying complexity and sophistication, to state-of-the-science probabilistic human exposure and dose models, to personal exposure measurement studies) have been explored. Outcome data bases (e.g., environmental or public health data) are also examined; stratifying or matching the outcome data with an appropriate exposure metric is often limited by the content, sparseness, or other restrictions on the outcome data sets.

The efforts to evaluate the value of improved exposure metrics on the ability to relate those metrics with outcomes in complex systems have met with varying degrees of success. This work describes the results of recent efforts, mostly involving air pollutants, to improve the sophistication in the exposure estimate and classification in order to improve the quality of associations between exposure and outcomes at the end of the complex systems, both human and environmental

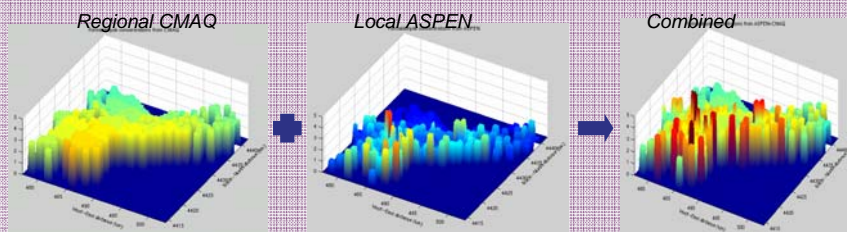
Better Exposure Estimates Spatial & Temporal Resolution

Integrating monitoring and modeling:

Observations for ground truth, models for spatial profiles and temporal patterns



Combining regional scale fused data with local scale models:



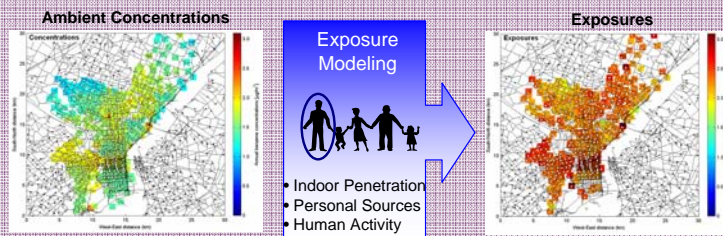
Apply human exposure models, improving exposure factors systematically to account for movement across areas and exposure events and processes:

$$E = \frac{1}{T} \left(\sum_j C_j t_j \right)$$

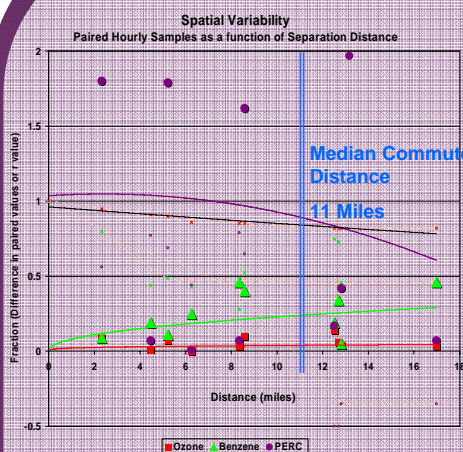
Exposure is the time-weighted sum all exposures from the different microenvironments in which a person spends time.



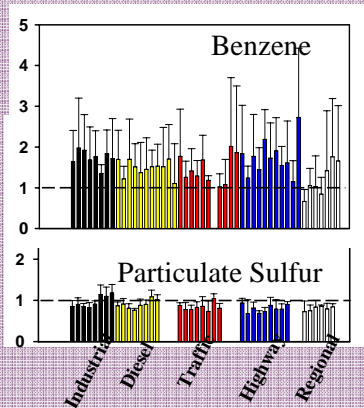
Use census data & LandScan data to improve travel profiles for work, school, shopping, recreational. Move population into / out of polluted areas throughout day.



Pollutant Variability



Relative change in concentration of ozone, benzene, and PERC plotted as a function of distance between sampling sites. Trend lines illustrate that ozone is consistent and well correlated across the urban area. Benzene is more variable, but relatively consistent across the urban area. PERC is highly variable and even negatively correlated between sites. Contemporaneous 1-h samples collected in Atlanta, GA. Assumes isotropic gradients.



Ratio and variability of concentrations measured at an ambient monitoring site and other locations dominated by specific source types. Particulate sulfate is a stable component of regional fine PM: Benzene is associated with local sources across the urban area and is more variable. 24-h samples collected in Detroit, MI. (Source: Ron Williams, NERL, EPA)

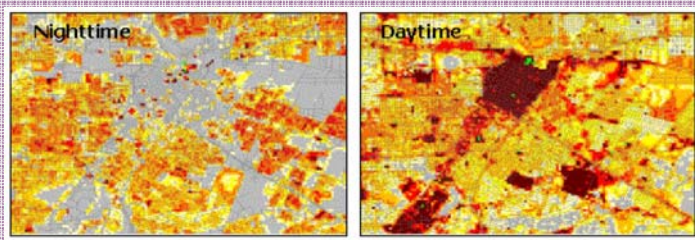
Relating Public Health Data & Environmental Data

Much of the available public health data represent events like hospital and Emergency Department (ED) visits. We and our collaborators have tended to use ED visits for illnesses like asthma, cardiovascular events, or pulmonary illness. Often the data include: a count of the events, by diagnoses or illness, on a particular date, at a particular hospital or ED. The location of facility is known, but information about the patient (e.g., their residential address) is often protected for privacy reasons or may be aggregated to the zip code or county level. Additional information that would be useful for estimating or stratifying exposures, like smoking habits, commuting patterns, pesticide usage habits, or occupation, are often not available.

Daily counts at each ED represent the small fraction of a large population who become sick enough to visit an ED on a particular day. The health data are, therefore, naturally integrated over a large population and represent the health outcomes of people who live across a fairly wide area (US population of 291 million people & 7569 hospitals = 38,500 per hospital: at US urban average of ~5500 people per square mile, this represents an area of 7 sq. mi., or a square ~ 4¼ km per side: a census tracts usually have 2,500 – 8,000 residents). If one is to correlate the ED counts with environmental data (e.g., exposures to a particular air pollutant), one would expect a valid relationship only for pollutant exposures that affect the population exposure across the area. Many "non-ambient" exposures are un-correlated with ambient exposures and lead to a consistent distribution of exposures for a population (even across cities) from day-to-day: as such, those "non-ambient" exposures would not be expected to correlate with the spatially-distributed public health data in a temporal analysis. In addition, the public health data represent daily (or sometimes longer) totals, integrating responses for at least 24 hr, and are confounded by a potential lag between exposure and onset, and between onset and the very "human" decision to go to the ED.

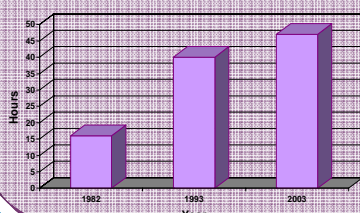
Results are still preliminary, but improved concentration data seems to improve correlations with public health data. Higher resolution on the spatially-resolved data may be of limited benefit, however.

Humans Move through the Environment



Nighttime vs. Daytime Population Densities calculated for Houston, Texas by LandScan population distribution model. (90 m grid cell. See www.ornl.gov/gist)

Delay due to Congestion Annual Average – 85 US Cities



The Average US Driver
Spends 55 minutes per day behind the wheel
Drives 29 miles a day
Only 15% of trips are for commuting – median commute distance of 11 miles
45 % of daily trips are taken for shopping and errands
27 % of daily trips are social and recreational

References

- National Household Travel Survey, Bureau of Travel Statistics
- 2005 Annual Urban Mobility Report, Texas Transportation Institute
- Ott et al., JAWMA, (2000), 1390-1406.
- Wilson and Brauer, JESEE, (2006), 264-274.

