A REPORT TO THE

U.S. CENTERS FOR DISEASE CONTROL AND PREVENTION

HEI/CDC/EPA WORKSHOP ON METHODOLOGIES

for

Environmental Public Health Tracking of Air Pollution Effects

January 15-16, 2008

CDC

HEI

EPA United States Environmental Protection Agency

A Report to the US Centers for Disease Prevention and Control

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EXECUTIVE SUMMARY

In January 2008 a two-day workshop, jointly organized and sponsored by the Health Effects Institute[1] (HEI), the US Centers for Disease Control and Prevention (CDC) and the US Environmental Protection Agency (US EPA), brought together representatives of state and national public health and environmental agencies and academic researchers from the United States, Canada and Europe to discuss key methodologic issues for the further development of the CDC's Environmental Public Health Tracking Network (EPHTN). One objective of the EPHTN is building a national infrastructure that will enable ongoing, periodic and timely analyses of the health impacts of air pollution at the state and local levels. Such an infrastructure would facilitate timely evaluations of the effects on public health of actions taken to improve air quality at the national, state and local levels. To provide robust estimates of the health impacts of air pollution that will be useful to stakeholders, methods must be used that address the strengths and limitations of purely local analyses or of external (e.g. national) analyses.

Building on previous work of the EPHT program and US EPA, the workshop was intended to consider suitable methods and further the development of indicators of the health effects of air pollution suitable for public health tracking of air pollution impacts at the state and local level. This report summarizes the workshop discussions and presents its recommendations. It is intended to serve as a basis for detailed guides, protocols, and tools, commissioned by CDC, which will enable the ongoing and consistent implementation of health impact tracking work by the state agencies.

Workshop participants comprised selected EPHT program participants, outside experts, and representatives of CDC, US EPA and HEI. Outside experts were identified based on their extensive experience in the development and application of statistical and epidemiologic tools for air pollution health impact assessment (HIA) in both academic and policy settings in North America and Europe.

Workshop participants were charged with producing recommendations for analyzing linked air quality and health data to estimate and track over time health impact indicators for two pollutants: fine particulate matter ($PM_{2.5}$) and ozone for use at the U.S. state and local levels, and for communicating the results of the analyses to stakeholders. Specifically, they were asked to recommend: 1) approaches for using analyses of state data to generate state and sub-state impact estimates for acute effects of air pollution; 2)

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[1] The Health Effects Institute is an independent, nonprofit organization chartered in 1980 to provide high-quality, impartial, and relevant science regarding the effects of air pollution on health. Supported jointly by the U.S. Environmental Protection Agency and industry, and periodically by other domestic and international partners, HEI provides science to inform decisions that are directly relevant to regulation and other actions to improve air quality.

approaches for using quantitative estimates of the relationship between air pollution exposure and health outcomes from the scientific literature to generate estimates of the acute and chronic health impacts in local areas; and 3) approaches to communicating the estimates and their limitations to stakeholders.

MAJOR CONCLUSIONS AND RECOMMENDATIONS

- Workshop participants emphasized the important potential contribution of the EPHTN, noting that future progress in public health protection will likely require improved understanding of local sources and control measures that require the engagement of local stakeholders, and that providing timely and locally relevant data on air pollution health impacts will be a motivating element of such engagement.
- However, the workshop concluded that in the context of health impact assessment for $PM_{2.5}$ and ozone purely local analyses, i.e., analyses that use only the air pollution and health data from a single geographic area, are unlikely to provide robust estimates of the relation between air pollution and acute and chronic health effects at the local level, although they may be appropriate for other research or surveillance applications as noted on page 17 and by Talbot et al (Annex B5). Therefore, it is essential that various methods of "borrowing strength" from other evidence be used to make such estimates when quantifying local public health impacts.
- The workshop recommends that the EPHT program should develop tracking of air quality health impacts incrementally. Initial focus should be on those activities/products that are most feasible in the near-term in order to provide evidence of the future value of the program.
- An initial goal should be the development, testing and application of a methodology for local health impact assessment in selected locations that uses quantitative estimates of the concentration-response relationships between air pollution exposure and health outcomes from the scientific literature. Clear operational guidance for applying the method and communicating results should be provided.
- In the longer term, a network of EPHT programs should develop analyses to produce cross-sectional estimates of local CR (concentration-response) functions that use methods that draw strength from pooled evidence across locations. Once established, this type of network could support longitudinal analyses that track the impact over time and thereby provide an assessment of the effectiveness of local, regional, and national air quality management initiatives.
- Developing estimates using local data of the relationship between air pollution exposure and health at the state and sub-state levels will initially require considerably more methodological groundwork than will health impact assessment using published concentration-response estimates. In addition, this approach requires a process that ensures standard methods

for data preparation and analysis across states, while addressing the requirements of data stewards in each state to ensure confidentiality.

- Assessments of the health impacts of air pollution have quantified impacts variously, in terms of numbers of attributable deaths and/or other adverse health outcomes, years of life lost (or saved), and loss (or gain) of healthy life expectancy. Which metric(s) best quantify the impacts of air pollution remains a controversial question among technical experts and policy makers. It is also not clear which metrics are the most effective for communication to diverse stakeholders, including the lay public. The EPHT should review the current experience with regard to choice of air pollution health impact metrics and the way in which they are communicated, with the goals of: 1) achieving consensus on the best approaches for the EPHTN; and 2) identifying critical knowledge gaps that could be addressed with additional research or methods development.

- The EPHTN aims to produce state and sub-state level estimates of the effects of the health impacts of exposure to air pollution. Providing a complete and straightforward account of the uncertainties in those estimates is critical to the overall transparency and credibility of the tracking network's results, but presents considerable challenges for communicating both the extent of the uncertainties, and their implications. The CDC Environmental Public Health Tracking Program should review the current experience with regard to efforts to communicate uncertainty in estimates of health effects and health impact assessments of environmental hazards, with the goals of: 1) achieving consensus on the best approaches for the EPHTN; and 2) identifying critical knowledge gaps that could be addressed with additional research.

- Communication among different agencies conducting health impact assessments is also needed. Currently in the US, health impact assessments of exposure to air pollution are being carried out by agencies at different levels, including US EPA, CDC, states and municipalities. The tracking program should work with involved agencies to avoid, if possible, methodologic inconsistencies that could produce artifactual differences in impact estimates. A well-developed communication strategy about health effects and impacts of air pollution, coordinated with other relevant agencies such as US EPA, should be an integral part of the EPHT.

INTRODUCTION

The United States has made considerable progress over the past 50 years in reducing levels of health-damaging ambient air pollution. However, National Ambient Air Quality Standards (NAAQS) for fine particulate matter ($PM_{2.5}$) and ozone are currently exceeded in some areas of the country, and exposure to air pollution continues to affect the health of the US population in terms of increased mortality and morbidity from cardiovascular and respiratory disease. Because the mission of CDC's Environmental Public Health Tracking (EPHT) program is *"…to provide information from a nationwide network of integrated health and environmental data that drives actions to improve the health of communities,"* ambient air quality is a priority content area for EPHT, and informing and evaluating local pollution control efforts by providing stakeholders with timely and locally relevant information on the public health burden (e.g., in terms of cardiovascular and respiratory disease) of these pollutants is a key EPHT objective. As a result of a collaborative effort of CDC, US EPA and state EPHT programs, an infrastructure, the Environmental Public Health Tracking Network (EPHTN), is being developed that will enable ongoing, periodic and timely analyses of the health impacts of air pollution at the state and local levels. Such an infrastructure would facilitate timely evaluations of the effects on public health of actions taken to improve air quality at the national, state and local levels, part of a process that has been termed "accountability." (HEI 2003) The development of indicators that link data on air quality and health events is a critical component of the EPHTN.

The primary NAAQS are based on extensive evidence of serious public health impacts of criteria air pollutants, including $PM_{2.5}$ and ozone (US EPA 2004a; US EPA 2006). The implementation of the US NAAQS, including measures to reduce emissions from vehicles, electric power generating plants, industry, and other sources as well as changes in the US economy, has led to improvements in ambient air quality, which have been estimated to result in substantial public health benefits (US EPA 2004b; US EPA 2005a; US EPA 2007). While these improvements are projected to continue, increasing urban sprawl and traffic volume and congestion may be slowing progress and threatening future gains, especially in some regions (Frumkin et al. 2004). At the same time, evidence is growing of the importance of health impacts associated with intra-urban gradients in ambient air pollution, especially those related to traffic (Miller et al. 2007; Jerrett et al. 2005). Thus, future advances in public health protection will likely require improved understanding of local sources and control measures that impinge on state and local land use and transportation policy. The more such measures affect local stakeholders, the greater the need for their engagement in the process. Providing local stakeholders timely, understandable and locally relevant data on air pollution health impacts will be an important part of such engagement.

In January 2008 a two-day workshop, jointly organized and sponsored by HEI, CDC and US EPA, brought together representatives of state and national public health and environmental agencies and academic researchers from the US, Canada and Europe to further the development of indicators of the health effects of air pollution suitable for public health tracking at the state and local level, building on the work of the EPHT program to-date. The workshop discussed key methodologic issues for indicator development, and made recommendations regarding further development and application of indicators. The workshop was charged with providing a written report to CDC, summarizing its discussions and recommendations. This report is intended to serve as a basis for the development of detailed guides, protocols, and tools, commissioned by CDC, which will enable the ongoing and consistent implementation of health impact assessment work conducted by the state agencies.

BACKGROUND

The Environmental Public Health Tracking Program

Environmental public health tracking has been defined as the "ongoing collection, integration, analysis and dissemination of data from environmental hazard monitoring, human exposure tracking, and health effects surveillance" (Meyer et al. 2006; Environmental Health Tracking Project Team 2000). Consistent with CDC's model of public health surveillance, the communication of findings to those with a "need to know" (Thacker et al. 1988) is a key component. The tracking model defines the stakeholders who are the target of dissemination efforts broadly to include policy makers, government and non-government agencies, business, researchers, the media, and members of the public.

In 2002 the EPHT program began to establish a network of state and local health department tracking programs, in a capacity building and method piloting phase. The program moved to a network implementation phase in 2006 and is currently funding 16 states and one city health department to participate in the development of a national network of linked information systems that is expected to be launched in 2008. In addition to health departments, four academic partners have been funded to develop methods and contribute to local projects and evaluation.

Priority content areas of EPHT currently include air pollution, water quality, cancer, birth defects and other birth outcomes, lead poisoning, pesticides, carbon monoxide poisoning, and hospitalizations for asthma and acute myocardial infarction (AMI). For each content area work groups have been established comprised of state and local grantee representatives, federal program staff, and academic partners, including an Air Content Team focused on air quality and health. Their role is to set priorities, identify relevant datasets and to develop standards for data, metadata, analyses, indicators and reporting.

Tracking air pollution-related health effects: objectives of the EPHTN

The Air Content Team has identified three objectives for the EPHTN in order that it ultimately will be able to provide stakeholders at the state and local levels with periodic and timely analyses to address such questions as:

- What is the public health burden attributable to ambient $PM_{2.5}$ and ozone levels?
- How does the burden vary within and between states?
- Is the burden changing over time, for example in response to efforts to reduce air pollution levels and population exposure?

The objectives are:

1. To make available to EPHT programs data on ambient air quality, relevant health outcomes, and other data needed to support public health tracking efforts;
2. To estimate the health impacts of air pollution, focusing initially on the effects of $PM_{2.5}$ and ozone. Achieving this goal would entail estimating the effects of exposure at the state and sub-state levels, and quantifying the public health impacts of exposure in order to evaluate and guide prevention and control measures. EPHT might also serve to identify populations that are at especially high risk and information about previously unsuspected health effects that could then be pursued further.
3. To produce and disseminate findings to key stakeholders in the form of indicators and other reports.

Meeting these objectives requires the development of indicators that link air quality and health outcomes and methods for their analysis that can provide valid and acceptably precise estimates in a tracking context. The Air Content Team has proposed a set of indicators that link adverse health outcomes, including deaths, hospital admissions, and, in some states, other morbidity data, with estimates of ambient air pollution. These indicators focus on fine particulate air pollution, $PM_{2.5}$, and ozone because of their well-established links to serious adverse health effects, and because, as noted above, the NAAQS for these pollutants are currently exceeded in many areas of the country. The EPHT program has also supported work on the analysis of these indicators in a tracking context. Details on these activities and progress to date are described in presentations (Annexes D1-D3), in a working paper (Annex B5), and by Booth et al. (2005).

Meeting the challenges in measuring the public health burden of air pollution at the state and local level

The environmental health indicators proposed by the Air Content Team that will use linked air pollution and health data (i.e. 'linked indicators') are more complex than purely descriptive measures such as numbers of residents in counties where air pollution levels exceed NAAQS criteria. The Air Content Team and CDC agreed that further work is needed to address methodological issues and ensure that the analyses conducted as part of EPHT program will yield robust, public health relevant estimates of the health impacts of air pollution that will be useful to stakeholders. Previous health impact assessments of air pollution conducted in Europe, the US, and Canada have grappled with these issues (LeTertre et al. 2005; USEPA 2005b; Burnett et al.2005). The current workshop was intended to bring this experience to bear on the work of the EPHT program, and to recommend approaches for implementation as the EPHTN continues to develop.

There are considerable challenges for developing and interpreting linked indicators for $PM_{2.5}$ and ozone. While an extensive body of research has established causal links between exposure to these pollutants and human health, concentration-response (CR) relationships quantifying these links have been shown to vary among geographic areas and over time for a variety of reasons. $PM_{2.5}$ and ozone may serve in part as indicators of complex pollutant mixtures and variation in composition by space and time may alter the relationship of concentration to health impacts. Additional modifying factors include population susceptibility, local health care utilization, services, and recording practices. In addition to these relatively stable local differences, exceptional local weather events or emission sources including forest or structural fires, or construction demolition may introduce different pollutant species or extreme pollutant levels within a local area. In addition, local interventions, including enhanced air quality alerts, land use and transportation changes, and control of local point sources may alter local air quality, and affect human exposure and its relationship to health.

Although estimates from purely local analyses should in theory best reflect local modifiers of a CR function, 'true' CR relationships are small relative to random error and potential bias affecting a single local study. Thus, estimates based on local data only may not accurately reflect the underlying CR relationship, and may even give indications of either anomalous "protective" effects or implausibly large effect estimates of risk. The methodological challenges are even greater for estimating time trends in the impact of air pollution on health at the state and sub-state levels. Additional challenges are posed by the need to meaningfully communicate to stakeholders the information gained from the EPHT analysis, while clearly setting out uncertainties and their implications.

CHARGE TO THE WORKSHOP

Workshop participants were charged with producing recommendations for analyzing linked air quality and health data to estimate and track over time health impact indicators for $PM_{2.5}$ and ozone for use at the US state and local levels, and for communicating the results to stakeholders.

Specifically, they were asked to recommend:

1) Approaches for using analyses of state-level data to generate state and sub-state impact estimates for acute effects of air pollution. These approaches will consider the use of state level analyses in the

context of other information including findings from other locations and published research;

2) Approaches for using external CR function estimates from the scientific literature to generate local estimates for chronic and acute effects. These approaches will need to consider local factors bearing on the applicability of published estimates.

In formulating approaches to health impact assessment, workshop participants were asked to consider the following issues:

- What available sources of monitored and modeled air pollution data are suitable and how should they be used?
- What are recommended approaches for assessing variation in air pollution impact between and within states?
- What are recommended approaches for assessing variation in air pollution impacts over time? How should temporal changes in demography and pollutant composition be addressed analytically?
- What resources are recommended to conduct health impact analyses, including technical expertise, data access, computational tools, infrastructure, and scientific review?
- What are key sources of uncertainty?
- How should uncertainty in estimates be characterized?
- What research is needed to improve environmental public health tracking of air pollution effects?
- What are the implications for national-level health impact assessment of state-level air pollution impact surveillance?
- Should methodologies be developed and widely deployed for use by non-epidemiologists to estimate local CR relationships involving $PM_{2.5}$ and O_3?

3) Approaches to communicating the estimates and their limitations to stakeholders. They were asked to consider the following questions:
   - How should quantitative impact estimates be expressed to stakeholders and the lay public (e.g., should risk estimates be presented as attributable morbidities or mortalities, years-of healthy life, or some other metric(s)?)
   - How should statistical or other uncertainties be presented so that they are neither over- nor under-emphasized?

THE WORKSHOP PROCESS

Participants

The participants comprised selected EPHT program participants, outside experts, and representatives of CDC, US EPA and HEI. Outside experts were identified based on their extensive experience in the development and application of statistical and epidemiologic tools for air pollution health impact assessment in both academic and policy settings in North America and Europe. Participants are listed in Annex A.

Jonathan Samet (Johns Hopkins Bloomberg School of Public Health) served as Chair. Thomas Matte (CDC), Aaron Cohen (HEI), Jeremy Sarnat (CDC, EPHT and Emory/Rollins School of Public Health), Fuyen Yip (CDC, Air Pollution and Respiratory Health Branch), Nicholas Jones (CDC, EPHT), and Fred Dimmick (US EPA) comprised a workshop Steering Committee with overall organizational responsibility for the workshop and served as Rapporteurs, with primary responsibility for drafting the workshop report.

Process
Prior to the workshop the outside experts were provided with detailed information on the EPHT project and the health impact indicators it has developed in order to ensure that their expertise and experience was focused on advancing the work of the EPHT.

To frame the relevant issues and suggest possible approaches for discussion eight working papers were commissioned and provided to all participants prior to the workshop. Authors were also asked to address future data acquisition and research needs relevant to their topic. The papers are included in Annex B, having in some cases been revised following the workshop.

The 2-day workshop program is presented in Annex C. The workshop began with brief presentations from EPHT representatives and outside experts. The goals and progress of the EPHT air content work group were described, including air pollution and health data being made available to the EPHTN, summaries of local analyses performed to estimate CR functions of the relation of $PM_{2.5}$ to AMI in New York State and ozone to asthma emergency department visits in Maine. Presentations on methodologic issues considered methods for pooling results of local analyses for acute effects, for applying external CR functions to produce local health impact estimates, and for tracking the change in CR functions over time and space for accountability purposes. Examples of health impact assessments from the US, Canada and Europe were also presented. These included HIAs concerning specific policy actions (such as London's low emission zone) as well as efforts to estimate the impact of achieving proposed air pollution standards. These presentation slides and summaries are provided in Annex D.

The participants then broke into three working groups in order to develop recommendations as discussed above. On the second day, the groups reported their recommendations to the entire workshop for discussion, refinement, and consensus.

Following the workshop, the workshop Steering Committee and Dr. Samet prepared this workshop report summarizing the workshop discussions and

recommendations. A draft was circulated to all participants for comment and revised as needed prior to submission of the final report to CDC.
The authors of the working papers and the Steering Committee agreed that the working papers included in Annex B were an important contribution in their own right to the literature on environmental public health tracking and health impact assessment, and Drs. Samet, Matte, Cohen and Sarnat were charged with seeking opportunities for their joint publication in the peer-reviewed literature along with a summary of this report.

GENERAL WORKSHOP CONCLUSIONS AND RECOMMENDATIONS

1. Future progress in public health protection will likely require improved understanding of local sources and control measures that require the engagement of local stakeholders.
2. Providing timely and locally relevant data on air pollution health impacts will be an important part of such engagement. Creating a network of state environmental health surveillance programs that can provide such data is consistent with the mission of the EPHT program. Because of variation in population susceptibility, health care and pollution composition, analyses using timely local data on ambient air quality and relevant health outcomes that can be routinely compiled by EPHT programs can be valuable for local health impact tracking when used as part of an appropriate analytic strategy.
3. However, purely local analyses, i.e., analyses that use only the air pollution and health data from a single geographic area, are unlikely to provide robust estimates of local CR functions or health impacts of short-term exposure. Moreover, because studies of the effects of long-term exposure on chronic diseases are infeasible in most locales, purely local analyses to estimate CR functions for effects of longer-term exposure are not an option. Therefore, it is essential that various methods of "borrowing strength" from other evidence be used to estimate CR functions for health impact estimates.
4. The EPHT program should develop tracking of air quality health impacts incrementally. Initial focus should be on those activities/products that are most feasible in the near-term in order to provide evidence of the value of the program going forward. Feasibility depends on our current confidence in, and availability of, local data on air quality, health outcomes and CR function estimates.
    - An initial goal should be the development, testing and application of a methodology for local health impact assessments in selected locations using existing, peer-reviewed evidence as a source of CR functions along with clear operational guidance for applying the method and communicating results.
    - A network of EPHT programs should ultimately develop analyses for cross-sectional estimates of local CR functions that are planned and designed to draw strength from pooled evidence

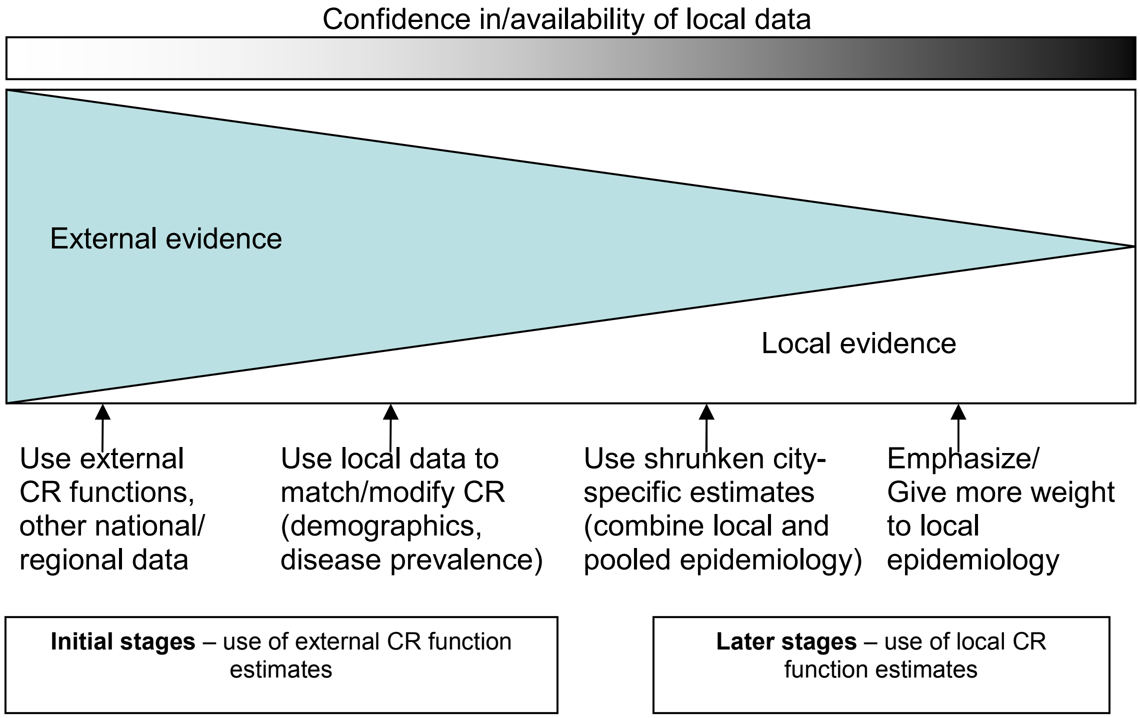
across locations using one or more methods presented at this workshop. Once established, such a network could support longitudinal analyses that are essential for assessing the effectiveness of local and, regional, and national air quality management initiatives.
    - Local CR function estimation for tracking purposes will initially require considerably greater methodologic groundwork, a process that ensures standard methods for data preparation and analysis, while addressing the requirements of data stewards to ensure confidentiality.
    - An incremental approach is discussed in more detail in the next section.

5. The continuing development of EPHT for effects of air pollution on health will require on-going close coordination between environmental and health agencies at the state and federal levels as well as collaboration with the research community. For example, both US EPA and the states will be conducting HIAs, albeit at different spatial scales. The methodologies should be consistent so that their results can be considered in a unified fashion.

AN INCREMENTAL APPROACH TO PUBLIC HEALTH TRACKING OF AIR POLLUTION

The workshop discussed a multi-stage approach to implementing state-level tracking of air pollution health impacts (Figure 1). An initial goal should be the development, testing and application of a methodology for local HIA in selected locations using existing, peer-reviewed evidence as a source of CR functions along with clear operational guidance for applying the method and communicating results (left side of Figure 1). In settings in which statistical power and resources are adequate for local epidemiology, a network of EPHT programs should in the longer term develop analyses for cross-sectional estimates (i.e., point estimates for the effect of air pollution across some period of time) of local CR functions that are planned and designed to draw strength from pooled evidence across locations (right side of Figure 1) using one or more methods presented by Fuentes at this workshop (Annex D6) and discussed in a working paper (Annex B1). Once the capacity for such planned, pooled cross-sectional analyses is demonstrated, such a network could support longitudinal accountability analyses as described by Burnett et al. (Annexes B8 and D8) to assess the effectiveness of local, regional, and national air quality management initiatives.

Figure 1: Conceptual model for staged development of air pollution health impact assessment for Environmental Public Health Tracking



Initial stage - Use of external CR functions for local health impact estimates

Application of external CR functions within an HIA framework has the advantage of being less methodologically complex than local time series or case-crossover analyses, while still being able to include information on local air quality and morbidity and mortality rates. The availability of software tools, such as EPAs BenMAP and WHO's AirQ, facilitates the computations. Nonetheless, this approach involves many decisions, assumptions and steps including the preparation of local data. The steps involved in a local health impact assessment based on external CR functions were described by Hubbell and Fann (Annex D7) and Levy (Annex D11) at this workshop, and are summarized below.

Steps in local health impact assessment based on external CR function estimates

- Characterize the study location in terms of relevant demographics and other population factors, region, and meteorology
- Identify appropriate air pollution CR function estimates from studies closely matching the local area.
- Analyze local morbidity and mortality data to compute background rates for populations applicable to the CR functions to be applied.
- Combine air quality data with population information to develop estimates of population-level potential exposure metrics (e.g. 8-hour maximum ozone, daily average $PM_{2.5}$).
- Define a counter-factual or comparison air quality scenario, e.g., a reduction from current ambient concentrations. (see glossary)
- Link changes in population exposure to ambient air pollution to CR functions and background rates to generate distributions of changes in the incidence of health outcomes.
- Develop summary statistics to describe health impact estimates and measures of uncertainty, e.g. mean, 95 percent confidence interval; and graphs, e.g. cumulative distribution functions and box-plots.
- Describe other dimensions of uncertainty qualitatively.
- Document all data sources and assumptions.

Although this general approach is suitable as an initial stage of health impact assessment for EPHT, a number of methodological issues must be addressed to ensure consistent, scientifically sound, well-documented estimates are produced with limitations that are characterized and communicated to stakeholders.

Methodological considerations
The following issues need to be considered carefully when using external CR functions for health impact estimates in a given locale.

- **Definition of 'local'** In "transferring" (Annexes B2 and D7) an external CR function estimate to compute a local health impact the analysis should where possible be consistent with the study methods from which the CR functions are derived. (Samet 2008) Since most air pollution epidemiologic studies have assigned exposure at the level of the city or metropolitan area or have used data from monitors whose measurements are correlated within a city over time, this approach is most suitable for generating estimates at the level of a city or metropolitan area.

The estimated health impacts of air pollution may vary within a city or metropolitan area because of geographic variation in the baseline incidence and/or susceptibility, or because of intra-urban concentration gradients. As noted by Levy (Annex D11) a city-wide estimate of impact may not be sensitive to whether the analysis considers only the average background disease rates across a city, but the estimated distribution of impacts within a city population may be highly sensitive to differences in background incidence and susceptibility. Reliable data on morbidity and mortality rates in subpopulations will be available for some health conditions, and these data can be used to directly capture variability in disease incidence/prevalence or to model this variability stratified by geography and demographics. In contrast, sufficient monitoring data to characterize intra-urban exposure gradients are generally limited or not available, making it necessary to rely on modeled concentration data to capture exposure differences in within-city impact analyses. Land use regressions and related techniques can provide such information in some settings, although the relative spatial homogeneity of $PM_{2.5}$ and ozone in many settings implies that such analyses may not be necessary for health impact assessments. Impact estimates outside urban areas may be limited by the lack of ambient monitoring data, requiring the use of modeled ambient concentration data, which is discussed below.

- **Source of ambient pollution concentration data** Most epidemiologic studies that are used to derive CR functions are conducted using a limited number of fixed site monitors to estimate exposure for a city or metropolitan area. A local HIA using an external CR function should therefore attempt to mimic this exposure assessment by using local, fixed site ambient monitors designed to track population exposure for a city or metropolitan area for which a HIA is being conducted. A drawback of this approach is that it precludes HIA estimates for large areas of many states that are not in close proximity to a metropolitan area. Deterministic model-based (e.g. Community Multi-scale Air Quality or CMAQ) or statistically-based (e.g. Hierarchical Bayesian) estimates could be used to provide estimates of ambient pollutant concentrations where such gaps exist (see White Annex B3; Dimmick Annex D). However, such estimates should be used cautiously as they may introduce additional analytical uncertainty and have not been validated.

- **Selection of CR functions from the literature** Assessing transferability of estimates is perhaps the most crucial step in the process and the one that may present the greatest barrier to consistent implementation by EPHT programs. Factors to consider include: regional geographic differences in pollutant mixture and particle composition, population demographics, meteorology and its impact on behavior and exposure, housing characteristics such as prevalence of air conditioning, and health care factors such as use of medications that may modify observed CR associations (e.g., statins). The applicability of estimates from chronic exposure cohort studies is also influenced by the characteristics of the cohort population. For example, the American Cancer Society cohort (Pope et al. 2002) was shown to include lower proportions of low-income, minority participants than are found in many cities.

- **Tracking health impacts over time** While external CR function health impact assessments can be repeated over time as one way of estimating potential benefits of improving air quality (or harm from worsening air quality), this approach has important limitations compared to longitudinal "accountability" studies designed to assess the impact of specific pollution control strategies (HEI Accountability Working Group 2003). Without information on temporal trends in CR functions, such serial estimates will only vary as a function of ambient pollution concentrations and local incidence rates. The effects of meteorology on ambient pollution concentrations, and of changes in health care on local incidence rates, further complicate the interpretation of serial HIA estimates.

Near-term implementation recommendations

1. EPA and CDC should develop specific operational guidance for implementation of health impact assessment using external CR functions. The guidance should include:

    a. A library of recommended CR functions classified based on geographic, demographic, housing, climate, pollutant composition and other variables affecting transferability of estimates. In addition, the data that health tracking programs should use to characterize their populations should be described along with a clear process for mapping these characteristics to suitable CR functions.

b. Preferred methods applicable to each CR function of assigning ambient concentration estimates using monitored data where available and modeled data where not available.
c. A standard set of counterfactual (i.e. comparison) ambient pollution scenarios and recommended methods for operationalizing them in the HIA analysis.
d. Standard procedures for preparing health outcome and air pollution data and computing local background incidence rates.
e. Standard procedures for computing uncertainty in HIA estimates.
f. Standard procedures for conducting sensitivity analyses.
g. A template for reporting the findings of HIA, including quantitative and qualitative assessments of uncertainty.

2. EPA's BenMAP software provides a useful framework and flexible computational tools for implementing HIA based on the external CR function approach. It could, therefore, be adapted for use in environmental public health tracking, provide that clear guidelines were developed for its use in this context. .

3. CDC and EPA should assess feasibility of implementation of HIA based on external CR functions by tracking programs with current resources and staffing and take steps to address any gaps.

4. CDC and EPA should implement training and provide ongoing technical assistance for tracking program staff implementing HIA based on external CR functions.

5. The guidance and training developed should be piloted in selected states and refined based on lessons learned.

6. The guidance should be peer reviewed and periodically re-reviewed to enhance the confidence of tracking programs and stakeholders that HIAs are based on scientifically sound methods.

Improving health impact assessment based on external CR functions and transitioning to local analyses

As tracking programs implement HIA based on external CR functions specific limitations of available local data will likely become apparent, serving to inform efforts to collect key data and conduct additional analyses. For example, air conditioning prevalence may modify CR functions, but timely local data on air conditioning prevalence may not be available. Local surveys may be conducted to fill this information gap. In other cases, limitations of available ambient monitoring data or modeled estimates may be shown to be a key source of uncertainty in health impact estimates, thereby driving efforts to enhance monitoring or validate modeling. Another way in which improvements may occur over time is through local analyses that help inform decisions about which CR functions available from a library of published estimates, such as that provided by BenMAP or similar programs, would best correspond to local conditions. Such local analyses might also indicate the need to consider specific features of the local population when estimating health impacts within a given area.

While the focus of health impact assessments initially will be on widely available data, including mortality, hospital admission, and increasingly, emergency department visits, these outcomes are influenced by changes in health care practices and improvements in treatment. Tracking programs should explore the feasibility of monitoring data on other health endpoints, such as school absence, bronchodilator medication use, or clinic visits that may be more sensitive to pollution effects. The increasing availability of electronic health records may facilitate such efforts.

EPA should further develop and evaluate methods that improve the spatial and temporal resolution and gaps in the ambient monitoring data to assist in future HIA analysis. Improving coverage outside of urban areas and resolution of intra-urban concentration gradients are both priorities. Efforts should include further evaluation of existing models and methodology such as CMAQ and HB to better characterize uncertainty and applicability to HIA. As experience is gained in computing local HIA and communicating the results to stakeholders, information gaps and priorities for analyses needed can help inform the next stage of tracking, which is described below

Later stage – Use of CR function estimates from local analyses

Given the many factors bearing on transferability of external CR function estimates to a local setting, using local analyses to contribute to CR estimates is a more direct, though more technically complex, method for addressing local factors. New York State and Maine analyses (Annexes D1 and D2) presented at this workshop serve as examples of local analyses conducted for tracking objectives. While the local data they employed require no assumptions about transferability, the results serve to illustrate the limits of purely local analyses. In New York State, the reported risk estimate between ambient $PM_{2.5}$ measured in urban areas and AMI was consistent with other published findings, but the estimate was imprecise and not statistically significant. The results also suggested that some subgroups were at greater risk of ozone effects, but again limited power of the local data precluded firm conclusions. In Maine, ambient ozone concentrations were directly related to asthma ED visits in 2000-2002, but the findings suggested an anomalously protective (though not statistically significant) association in 2003.

These local examples reinforce lessons learned from prior multi-city analyses (Samet et al. 2000; Katsouyanni et al. 2001): because the estimated CR functions relating air pollution to health outcomes are often modest in relation to unexplained error, purely local estimates typically cannot support robust health impact estimates in most locations. [2] It is therefore essential that one of the available statistical approaches as were described at this workshop by Fuentes (Annexes B1 and D6) should be used to allow local estimates to draw strength from other data.

Methodological considerations

- **Definition of 'local'** The definition of 'local' should ultimately be population-based with the option of specific states using alternative levels of scaling. Realistically, the highest degree of spatial resolution for a local analysis in most cases is limited by the current resolution of available ambient pollution data to either the county or city level. Implicit in this definition is the issue of analytical uncertainty.

- **Source of ambient pollution concentration data** As with external CR function applications, data from ambient monitoring networks are often available for large metropolitan areas with limited coverage outside of urban areas. While either integrated (AQIS) or continuous (AIRNow) monitoring data is available, as noted by Warren White (Annex B3), the former is designed for assessing compliance with NAAQS whereas continuous monitoring data can provide better spatial and temporal coverage useful for local time series or case-crossover analyses. Approaches that have been applied to improve spatial resolution, especially for intra-urban exposure gradients, include kriging and land-use regression modeling. These methods have been most useful for estimating average ambient concentrations in chronic exposure cohort studies.

  CMAQ modeling has been used to provide greater spatial estimates of pollutant levels over longer periods of time, such as an ozone season. Given their reliance on relatively fixed source strengths, CMAQ and other meteorological-based models may underestimate temporal variability. Using these exposure estimates to derive a local CR function may, therefore, yield biased estimates. To address limitations of CMAQ estimates, there are efforts to use both ground level data from the AQS network with CMAQ estimates within an hierarchical Bayes (HB) modeling framework to generate a national, spatially-contiguous grid of $PM_{2.5}$ and O_3 concentrations. In collaboration with

[2] The limitations of purely local analyses were discussed in the context of analyses to produce health impact estimates for two air quality measures, ozone and $PM_{2.5}$, for which causal associations with health outcomes have been clearly established and to disseminate these estimates directly to a wide range of stakeholders. As discussed by Talbot and Haley (Annex B5), local analyses may be valuable for a range of other research and surveillance goals, such as developing or testing novel hypotheses about the interaction of air pollution and weather (Ito et al.2007) or studying the impact of a unique local event (Friedman et al. 2001).

the tracking program, the EPA has explored the use of the HB estimates in case-crossover analyses of acute effects of $PM_{2.5}$ and O_3 on hospitalizations (Boothe et al., 2005; Annex B5). Further validation and methodologic study is needed to understand the value of these statistical estimates in analyses to generate local CR functions.

Several previous studies have addressed the means for assigning air pollutant exposures for a population in a local analysis and the impact of exposure measurement error that occurs when using limited ambient monitoring or modeled data to estimate true population exposure (Zeger et al. 2000; Dominici et al. 2000; Meng et al. 2005; Sarnat et. al. 2007; Sheppard et al. 2008). Fuentes (Annex B1) discusses the importance of quantifying exposure assessment error in local analyses and notes that this may be a substantial source of uncertainty for a HIA. For locations with either limited or non-local pollutant monitoring or for locations using modeled pollutant estimates solely, this source of error may be especially pronounced relative to other potential error sources.

Relatively few epidemiologic studies to date have actually attempted to adjust their results for measurement error in exposure, and methods that might be applicable in a tracking context have yet to be developed. However, methodological studies indicate that it may be possible to develop an approach to predict the likely effect of exposure assessment error on an observed CR function for a given locality. It has been shown, for example, that for analyses of short-term changes in pollutant levels and corresponding acute health impacts, exposure measurement error may bias point estimates of health impact toward the null and reduce precision, though the implications of measurement error depend on associations between ambient and personal concentrations and among measurement errors of co-pollutants (Zeger et al. 2000; Dominici et al. 2000; Sarnat et. al. 2007; Sheppard et al. 2008). One recent large scale study of short-term exposure and hospital admissions has implemented an approach based on regression-calibration (Peng R et al. 2008, Carroll RJ et al. 2006).

In addition to methodological complexity, another barrier to routine implementation of adjustment for exposure assessment error is the limited availability of exposure assessment validation data comparing ambient monitor or model data with measured personal exposures for a population subset. Since validation studies are often costly and time-consuming, it may be necessary to develop an approach for choosing validation results from studies conducted similar locations, similar to the approach for choosing an appropriate external CR function in the previous section.

- **Health outcome data** Air quality has been linked to several health outcome measures including mortality from cardiovascular and respiratory disease, hospitalization, and ED visits, as well as adverse birth outcomes and defects. Given the multiple sources of these health data within a locality (e.g., hospitals, clinics, insurance records) care is needed to ensure there is adequate coverage and a consistent degree of data quality across the sources.

- **Analytical methods for addressing uncertainty in local analyses** Sources of uncertainty within local analyses may exist in the exposure assignment, health outcomes recording, or generation of the CR function. To address such uncertainty, several multi-stage methods that incorporate information across space and time, including hierarchical Bayesian approaches, are acceptable for pooling evidence from local analyses. Generating shrunken CR estimates of risk using pooled observations were cited as a means of reducing model uncertainty in a local analysis, especially for locations with limited local data. Various methods are discussed more fully by Fuentes (Annexes B1 and D6). Multi-stage modeling may be applied to estimating exposures as well as generating local CR functions. A strategy that shares full information on local distribution of modeled input and outputs (e.g., ambient concentrations, local characteristics), not just summary statistics, can enhance pooled analyses. The use of full distributional information for estimating local exposures can be used to reduce as well as communicate the levels of uncertainty to stakeholders in the HIA results. For example, if an improved estimate of a spatial correlation would substantially improve precision of a localized estimate, studies can be conducted to more accurately estimate the correlation. Ultimately, the feasibility of implementation in the context of EPHT may determine which method is most suitable.

- **Tracking key air pollution events** Unique local events can have an impact on local CR functions and in some cases provide natural experiments for testing hypotheses about local interventions (Friedman et al. 2001). To anticipate such analyses EPHT programs could develop a 'key events log' describing changes affecting either pollutant levels or health outcomes. These events can subsequently be used in multi-stage modeling approaches as a means of explaining observed uncertainty in the model parameters and local CR function.

- **Resources needed to conduct local analyses** Despite the potential advantages of using local analyses to estimate air pollution-related health risks, the proposed approaches are analytically intensive. A major barrier to near-term implementation of local analyses is that many states lack the resources of time, personnel and expertise needed to conduct these analyses. Training, streamlined toolkits (e.g., the case-crossover software developed for EPHT), and a process for ongoing technical assistance and expert review of analyses are among the steps needed to address this barrier.

Implementation recommendations

1. Routine local analyses to estimate CR functions for health impact estimates and tracking in the EPHT program should be undertaken in the context of an analytic plan and process that anticipates pooling local analyses using one or more acceptable methods described at this workshop.

2. Whatever method is adopted for pooled analyses, provisions should be made for sharing full information on the local distributions of modeled input and outputs (e.g., ambient concentrations, local characteristic), not just summary measures.

3. The CDC EPHT program should address the level of resources needed to generate locally derived CR functions before routine local analyses are implemented. Substantial resources will be needed to support model development, use, promotion and oversight. Recommended steps include:
    a. Assess EPHT program capacity for supporting the needed analyses.
    b. Evaluate models for government-academic partnerships to provide needed technical capacity.
    c. Develop training for data users. These can both be in the form of workshops for state EPHT grantees and online resources for public stakeholders.
    d. Develop a streamlined toolkit for generating local CR functions. The case-crossover software developed by investigators working on the PHASE project serves as an example that could help attain method consistency (see Talbot et al. Annex B5). The software should have detailed guidance documents and open source codes.
    e. Create a means for oversight of the modeling process. Oversight should exist, *a priori*, as well as for the output based on a peer or institutional review model. Recommendations for modifying and revising the model toolkit should be a goal of the oversight process.

4. A log of key local events that may impact air quality, relevant health outcomes, and/or local CR functions should be kept by states and made available nationally. Such data could be used in pooled analyses as described above and could be a resource to identify opportunities for researchers to work with EPHT programs to test important hypotheses and evaluate interventions.

5. Models for concentrations, exposures or CR should evolve. Start with existing models, use multi-stage methods, evaluate with pilot data, and then adapt the models as indicated.

RECOMMENDATIONS ON COMMUNICATIONS ISSUES

The National Environmental Public Health Tracking Network (EPHTN) seeks to inform and evaluate local pollution control efforts by providing stakeholders with timely and locally relevant information on the public health burden of PM and ozone. Developing an overall communications strategy is a critical task of the EPHTN, in no small part because a successful strategy will require coordination among many layers of public health and environmental health agencies and systems. Communicating estimates of health impact generated by linking air quality data and health data, and the limitations associated with such estimates, will be a critical component of such a strategy.

Methodological considerations

- **Choice of metrics to quantify and communicate health impacts.** Air pollution health impact assessments at the state and sub-state levels should be a major focus of the EPHTN going forward. There has been considerable US and international experience with such assessments, leading examples of which were discussed at the workshop (Annexes B2, B7, B8, D7, D8, D9, and D10). These assessments have quantified health impacts of exposure to air pollution variously, in terms of numbers of attributable deaths and/or other adverse health outcomes, years of life lost (or saved), and loss (or gain) of healthy life expectancy. Which metric(s) best quantify the impacts of air pollution remains a controversial question among technical experts and policy makers (McMichael et al. 1998; Brunekreef et al. 2007, Rabl 2005). Various counterfactual or comparison scenarios have also been used, for example estimating the health impact of actual ambient pollution relative to a National Ambient Air Quality Standard, a proposed standard, or "naturally occurring background" levels of a pollutant.

  The range of audiences and uses of information from health impact assessments (Annex B6) further complicate the selection of health impact metrics. Although the US EPA has conducted message testing regarding health impact measures using lay audience focus groups (personal communication, Susan Stone, US EPA), further research and testing is needed to provide definitive answers.

- **Coordination of communication efforts among agencies.** The workshop participants noted the importance of communication among different agencies responsible for tracking air quality and health impacts. Currently in the US, health impact assessments of exposure to air pollution are being carried out by agencies at different levels, including US EPA, CDC, states and municipalities. It would be desirable to avoid, if possible, methodologic inconsistencies that could produce artifactual differences in impact estimates. At a minimum, CDC and Tracking Program participants will need to be able to explain why estimates produced by different agencies and at different times differ. There will also be different layers of data that will need interpretation. Metadata should be used but may also need interpretive messages for audiences to fully understand. A good example might be the health impact statements EPA provides with the Ambient Air Quality Standard.

- **Communicating uncertainty in health impact assessments** The EPHTN will produce state and sub-state level estimates of exposure to air pollution as well as estimates of the health impacts of such exposures. Providing a complete and "honest" account of the uncertainties in those estimates is critical to the overall transparency and credibility of the tracking network's results, but presents considerable challenges for communicating both the extent of the uncertainties, and their implications. Both types of estimates, even if carefully made with state-of-the–art methods, will be subject to uncertainty from various sources, as discussed above and in working papers prepared for this workshop (Annexes B1 and B2). In many air pollution health impact assessments the results have been presented simply as a point estimate of the number of deaths attributable to exposure, along with a confidence interval that reflects only the precision of the relative risk used to calculate the attributable number. Other sources of uncertainty, such those contributed by the exposure assessment methods, have often not been taken into account.

  Fortunately, an increasing number of recent assessments have begun to present more complete estimates of uncertainty, using sensitivity analyses, or more complex statistical approaches to calculate an uncertainty distribution that simultaneously quantifies the contribution of several sources (Cohen et al. 2004; National Research Council 2002).

  Although there now exists a high degree of confidence regarding the adverse health effects of air pollution, workshop participants felt that messages about these effects should also inform the public about any relevant uncertainties. There is a considerable body of experience about the communication to diverse audiences of uncertainties in risk assessments of air pollution and other health hazards, including the European APHEIS project (Annex B7). In addition, CDC and state health departments have considerable experience with communicating uncertainty about a wide range of health and environmental concerns. What is lacking is organized knowledge about the communication of uncertainty as it applies to the effect and impact estimates that will be generated by the EPHTN.

- **Communicating uncertainty in comparisons by locale and time period** The EPHTN will ultimately feature health effect and impact estimates from various locales and time periods, making possible the comparison of different locales at one or more points in time. The workshop noted that the Tracking Program must devote additional attention to communicating the uncertainties in such comparisons, which pose unique problems, both scientific and political, with regard to differences that might be observed, and the potential misinterpretation of explicit or implicit rankings (Annexes B6 and D4). The workshop discussed options including comparison of each locale to a common standard, and graphical approaches such as those used by APHEIS (B7), but concluded that further focused methodologic work was needed.

- **Integrating health impact information into an overall communication strategy** Whenever air pollution information is communicated to stakeholders, questions about population health impacts should be anticipated. A network of tracking programs prepared to disseminate credible, locally relevant information on health impacts can take advantage of such ‘teachable moments’.

  For example, some air pollution exposure indicators being developed for the EPHTN reference the NAAQS. For geographic areas where ambient pollution does not exceed that NAAQS, stakeholders may incorrectly conclude that air pollution has no public health impact in their locale and that no public health rationale exists for further improvements.

  Significant and newsworthy events that affect air quality, such as major structural or natural fires, unusual weather events, or traffic mitigation measures, such as those implemented during the Atlanta Olympics represent another opportunity to inform stakeholders about local air quality impacts on public health. Planned observance days such as National Air Quality Week or Earth Day can provide opportunities to incorporate health impact information into air quality messages.

Implementation Recommendations

1. A well-developed communication strategy about health effects and impacts of air pollution, coordinated with other relevant agencies such as US EPA, should be an integral part of the EPHT.
2. Appropriate risk communication strategies should be incorporated where possible. These should take into account the perspectives and background knowledge of the various stakeholders.
3. The Tracking Program should review the current experience and research evidence, such as that developed by the US EPA (personal communication, Susan Stone, US EPA) and other evidence summarized in Annex B6, with regard to choice of air pollution health impact metrics and their communication in order to: 1) achieve consensus on the best approaches for the EPHTN; and 2) identify critical knowledge gaps that could be addressed with additional research.
4. Consensus approaches should be developed using a matrix format that identifies preferred health impact metrics based on audience type and intended use.
5. The Tracking Program should work with US EPA to coordinate methodologic approaches for health impact assessment with the

goal of identifying and resolving major inconsistencies in methodology.

6. The Tracking Program should plan ongoing evaluation of its communication efforts to assess reach, usefulness, and impact.
7. The Tracking Program should review the current experience with regard to efforts to communicate uncertainty in estimates of health effects and health impact assessments of environmental hazards, with the goals of: 1) achieving consensus on the best approaches for the EPHTN; and 2) identifying critical knowledge gaps that could be addressed with additional research.
8. Candidate approaches for communication of uncertainty should then be tested with diverse audiences representing major stakeholder groups.
9. The Tracking Program should support the development of methods for communicating the results of comparisons between locales and their uncertainties.

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GLOSSARY

Health impact assessment (HIA)- "A combination of procedures, methods, and tools by which a policy, program, or project may be judged as to its potential effects on the health of a population, and the distribution of those effects within the population."[3] In some cases of HIA for air pollution, the impact of current ambient air pollution levels relative to a counter factual air pollution scenario is estimated. In this case, the goal may be to evaluate the potential benefits of achieving a proposed air quality standard, or more generally a hypothetical improvement in air quality, without specifying the particular measures needed to achieve the improvement.

Health impact tracking - Ongoing, periodic estimation of health impacts over time.

Environmental Public Health Tracking (EPHT)- 'The ongoing collection, integration, analysis, and dissemination of data from environmental hazard monitoring, human exposure tracking, and health effect surveillance'.[4]

Environmental Public Health Tracking Network - A web-based distributed network being developed to provide for access and exchange of environmental data, health data, and tools for data analysis and visualization.

Environmental Public Health Tracking Program – A U.S. Centers for Disease Control and Prevention program the goals of which are to '1) build a sustainable national EPHT network, increase state and local EPHT capacity, (3) disseminate credible information, (4) advance environmental public health science and research, and (5) bridge the gap between public health and the environment.' The program advances its goals by providing grants to state and local health departments and schools of public health, by evaluating data sources and developing model data systems, and by fostering collaboration and partnerships among environmental agencies, health agencies, nongovernmental organizations and communities.

Concentration-response (CR) function - In the context of air pollution HIA, the CR function is a mathematical expression describing an estimated relationship between the ambient concentration of a specified air pollutant and the occurrence rate of a specified health outcome.

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[3] http://www.euro.who.int/document/PAE/Gothenburgpaper.pdf

[4] McGeehin MA, Qualters JR, Niskar AS. National Environmental Public Health Tracking Program: Bridging the Information Gap. http://www.ehponline.org/members/2004/7144/7144.html

Counter-factual air pollution scenario - A hypothetical distribution of the concentrations of an ambient air pollutant being compared to actual or estimated levels. The hypothetical distribution might describe air pollutant levels meeting a proposed standard, resulting from a specified program or policy action, or some other hypothetical scenario, such as pollution at naturally occurring background levels. The difference between the occurrence of a specific health outcome currently and that estimated to occur under the counter-factual scenario comprises the health impact estimate.

APHEIS – Air Pollution and Health and European Information System
A program funded by the European Commission in which governmental and research institutions across Europe collaborated to produce and disseminate estimates of the health impacts of air pollution to a range of stakeholders and policy makers.

Environmental health indicator - 'An environmental public health indicator (EPHI) provides information about a population's health status with respect to environmental factors. It can be used to assess health or a factor associated with health (i.e., risk factor, intervention) in a specified population through direct or indirect measures.' Indicators may reflect environmental hazards, exposures, health effects, or interventions. [5]

Linked indicator - In the context of EPHT, a linked indicator is an environmental health indicator that is derived from linked environmental and health data. For air pollution health effects tracking, linked indicators refer to measures of population health effect attributable to ambient pollution.

[5] http://www.cdc.gov/nceh/indicators/description.htm

LIST OF ANNEXES

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ANNEX B: Working Papers

B1. Fuentes M. Statistical issues in health impact assessment at the state and local levels.

B2. Hubbell B, Fann N, Levy JI. Methodological Considerations in Developing Local Scale Health Impact Assessments: Balancing National, Regional, and Local Data.

B3. White W. Considerations in the use of ozone and $PM_{2.5}$ data in exposure assessment.

B4. Bachmann J. Air pollution forecasts and results oriented tracking.

B5. Talbot TO, Haley VB, Dimmick WF, Paulu C, Talbott EO, Rager E. Developing consistent data and methods to measure the public health impacts of ambient air quality for Environmental Public Health Tracking: Progress to date and future directions.

B6.Wartenberg D. *Communicating air quality health impact estimates and their limitations to stakeholders.*

B7. Medina S, Le Tertre A, Sklad M. The APHEIS Project: Air Pollution and Health – A European Information System.

B8. Shin HH, Stieb DM, Jessiman B, Goldberg MS, Brion O, Brook J, Ramsay T, Burnett RT. Measuring public health accountability of air quality management.

ANNEX C: Agenda

ANNEX D: Presentations

D1. EPHT air pollution & health tracking overview with New York examples Valerie Haley and Thomas Talbot, New York State Department of Health

D2. Ambient ozone and asthma-related emergency room visits: the Maine experience Chris Paulu, Maine Center for Disease Control & Prevention

D3. Characterizing air quality for environmental public health tracking. Fred Dimmick, Environmental Protection Agency

D4. Community air quality health indicators to stakeholders: It's up in the air. Dan Wartenberg, UMDNJ-Robert Wood Johnson Medical School

D5. NAAQS for epidemiologists. Warren H. White. University of California

D6. Statistical issues in health impact estimates at the state and local level. Montse Fuentes, North Carolina State University

D7. Methodological considerations in developing local scale health impact estimates using national/regional data Bryan Hubbell and Neal Fann, Environmental Protection Agency

D8. Air health indicator. Hwashin Shin and Richard T. Burnett, Health Canada

D9. Monitoring the impact of air pollution on public health in 26 European cities. Sylvia Medina, National Institute of Public Health Surveillance

D10. Chronic PM2.5 health impact assessment in European cities. Michal Krzyzanowski, WHO European Centre for Environment and Health

D11. Small area health impact assessment. Jonathan Levy, Harvard School of Public Health

D12. Evaluating traffic schemes in London. H. Ross Anderson. St. Georges University, London.

ANNEX A
Workshop Participants

Workshop on Methodologies for Enviornmental Public Health Tracking of Air Pollution Effects

January 15-16, 2008
Admiral Fell Inn
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ANNEX B1.

Fuentes M. Statistical issues in health impact assessment at the state and local levels.

ANNEX B

Statistical issues in health impact assessment at the state and local levels [1]

Montserrat Fuentes

Abstract

In this work we discuss the uncertainty in estimating the human health risk due to exposure to air pollution, including personal and population average exposure error, epidemiological designs and methods of analysis. Different epidemiological models may lead to very different conclusions for the same set of data. Thus, evaluation of the assumptions made and sensitivity analysis are necessary.

Short-term health impact indicators may be calculated using concentration-response (C-R) functions. We discuss different methods to combine C-R function estimates from a given locale and time period with the larger body of evidence from other locales and periods and with the literature. A shrunken method is recommended to combine C-R function estimates from multiple-locales. This shrunken estimate includes information from the overall and the local estimates, and thus it characterizes the estimated excess of risk due to heterogeneity between the different locations.

1 Introduction

In this manuscript we discuss relevant statistical issues in establishing the impact on human health of exposure to ozone, particulate matter and other pollutants at the state and local levels. A typical analysis consists of two stages, (1) exposure assessment and (2) epidemiological analysis relating exposure to the health outcome. We start with the exposure assessment in Section 2. In this section we discuss different approaches to estimate pollution exposure including: the use of monitoring data, spatial statistical interpolation methods,

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air quality numerical models, satellite data and probabilistic exposure models. We discuss advantages and limitations of each one of the approaches, and we end this section with a discussion of uncertainty in the exposure assessment.

In Section 3 and 4 we discuss health outcome analyses. In Section 3, we introduce two complementary statistical methods for risk assessment: a time-series based approach and a case-crossover design, which are equivalent approaches under some assumptions. We present uncertainty analysis for both frameworks.

In Section 4, we introduce different approaches for local concentration-response function analysis: local regression analysis, adjusted estimates using external C-R functions, shrunken approaches, and full Bayesian methods. We discuss uncertainty analysis for the C-R function.

2 Exposure assessment

Epidemiologic studies typically assess the health impacts of particulate matter and ozone using ambient concentrations measured at a centrally-located monitoring site, or at several sites located across the study area, to reflect exposures for their study population. The ability of these ambient concentrations to reflect actual pollution exposures for the study population generally depends on several factors, including the spatial distribution of the ambient air pollutants and the activity and home ventilation patterns for the study community.

One method to link personal exposure to ambient levels, and thus to the association between air pollution and the health endpoints, is to model exposure by simulating the movement of individuals through time and space and estimate their exposure to a given pollutant in indoor, outdoor, and vehicular microenvironments. The exposure model developed by the U.S. Environmental Protection Agency (EPA) to estimate human population exposure to particulate matter is called Stochastic Human Exposure and Dose Simulation (SHEDS-PM) (Burke, 2005) and the stochastic model for ozone is called Air Pollutants Exposure (APEX). They are both probabilistic models designed to account for the numerous sources of variability that affect people's exposures, including human activity. Daily activity patterns for individuals in a study area, an input to APEX and SHEDS, are obtained from detailed diaries that are compiled in the Consolidated Human Activity Database (CHAD) (McCurdy et al., 2000; EPA 2002). Although SHEDS and APEX can be valuable tools, human exposure simulation models, introduce their own uncertainties, and such models need to be further evaluated and their uncertainties characterized.

Most of the previous analyses of particulate matter (PM) health effects have been conducted in urban areas; very little is known about rural PM-related health effects. One reason for this is that monitoring data are sparse across space and time. For ozone, we lack of information for the winter months, since most monitoring stations only operate from May to September. Thus, EPA in collaboration with the Centers for Disease Control and Prevention (CDC), and three state public health agencies (New York, Maine, and Wisconsin) are working together on the Public Health Air Surveillance Evaluation (PHASE) project to identify different spatial-temporal interpolation tools that can be used to generate daily surrogate measures of exposure to ambient air pollution and relate those measure to available public health data. As part of the PHASE project, EPA is using statistical techniques (e.g. Kriging, see Cressie, 1993) to interpolate monitoring data at locations and times for which we do not have observations. EPA is also supplementing monitoring data with satellite data and atmospheric deterministic models (e.g., Community Multiscale Air Quality (CMAQ) models). These models run by EPA provide hourly air pollution concentrations and fluxes at regular grids in the U.S.. CMAQ uses as inputs meteorological data, emissions data and boundary values of air pollution (Binkowski and Roselle, 2003; Byun and Schere, 2006). These air quality numerical models provide areal pollution estimates, rather than spatial point estimates. Thus, we have a change of support problem (see e.g. Gotway and Young, 2002), since monitoring data and numerical models do not have the same spatial resolution. EPA in the PHASE project has adopted a hierarchical Bayesian (HB) spatial-temporal model to fuse monitoring data with CMAQ, using sound statistical principles (McMillan et al., 2007). The Bayesian approach provides a natural framework for combining data (see Fuentes and Raftery, 2005), and it relays on prior distributions for different parameters in the statistical model. The prior distributions could be space dependent and also substance dependent. So, it is important to use this framework with caution when applied to different geographic domains and different air pollutants. The potential bias in the pollution estimates as a result of the change of support problem is not taken into account in the PHASE project due to the computational burden. This might not cause a significant impact on the estimated exposure when the air quality numerical models are run at a high spatial resolution (i.e. grid cells of $4km \times 4km$). However, when CMAQ is run at a coarse resolution (e.g. grid cells of $36km \times 36km$), the change of support problem could result in biased exposure estimates.

The final product of the HB approach adopted in the PHASE project is a joint distribution of the concentrations of pollution across space and time. Since this distribution is likely to be non-Normal, just the mean of the distribution at each location and time is not necessarily a good summary. Alternative summaries should be considered, such as different percentiles. Ideally, one would like to work with simulated values from the distribution rather than just a summary of the distribution, because that way we could characterize the uncertainty in the exposure when conducting the risk assessment. This will be discussed in Section 4.

2.1 Uncertainty in the exposure assessment

The use of statistical models (e.g. kriging), air quality numerical models (e.g. CMAQ), or exposure models (APEX, SHEDS) to help characterizing exposure to ozone and particulate matter adds more sources of uncertainty to the human health risk assessment estimates, because these models have their own uncertainties. However, the air quality models can be valuable and a powerful tool to extend the concentration-response (C-R) function analysis to the national level and also for the times in which not enough monitoring data are available. The air quality models, based on the dynamics and mechanics of atmospheric processes, typically provide information at higher temporal and spatial resolution than data from observational networks. Errors and biases in these deterministic models are inevitable due to simplified or neglected physical processes or mathematical approximations used in the physical parameterization. The exposure models can be considered a powerful to characterize the exposures of the study population by taking into account human activities. The different sources of error and uncertainties in the exposure models (SHEDS, APEX) result from variability not modeled or modeled incorrectly, erroneous or uncertain inputs, errors in coding, simplifications of physical, chemical and biological processes to form the conceptual models, and flaws in the conceptual model. In particular, the uncertainty in the estimation of ambient air quality will be propagated by APEX and SHEDS. The APEX and SHEDS output could be also very sensitive to the uncertainty in the prior distributions used in the microenvironmental models. Evaluation of these air quality and exposure models would help to quantify and characterized the different sources of errors in the models.

In some cases, presenting results from a small number of model scenarios would provide an adequate uncertainty analysis for the air quality and exposure models (e.g. when insufficient information is available). In most situations, probabilistic methods would be necessary to characterize properly at least some uncertainties, and also to communicate clearly the overall uncertainties. Although a full Bayesian analysis that incorporates all sources of information may be desirable in principle, in practice, it will be necessary to make strategic choices about which sources of uncertainty justify such treatment and which sources are better handled through less formal means, such as consideration of how model outputs might change as some of the inputs vary through a range of plausible values.

These different sources of uncertainty in the estimated exposure due to the use of different interpolation techniques need to be taken into account when estimating the C-R function. When using a Bayesian approach to estimate the expose (e.g. HB-PHASE approach), the uncertainty in the exposure to some degree is characterized by the joint distribution of the exposure values. To the extend that is computationally feasible, the risk assessment should be conducted using the joint distribution of the exposure values rather than just means from that distribution.

Sensitivity analysis should be conducted to understand the impact of the uncertainty in the exposure estimates on the risk assessment, since it could result in over or under estimation of the risk.

3 Risk assessment

Time series analysis is a commonly-used technique for assessing the association between counts of health events over time and exposure to ambient air pollution. The case-crossover design is an alternative method, that uses cases only, and compares exposures just prior to the event times to exposures at comparable control, or *referent* times, in order to assess the effect of short-term exposure on the risk of a rare event (see Janes et al., 2004). Each technique has advantages and disadvantages (see Fung et al., 2003). The PHASE team has selected case-crossover rather than time-series analysis due to the shorter learning curve (easier to use), and because within one analysis the method can accommodate many time-series. It is important to keep in mind that the case-crossover design is equivalent to a Poisson regression analysis except that confounding is controlled for by design (matching) instead of in the regression model. Restricting referents to the same day of week and season as the index time controls for these confounding effects by design. Accurate estimates can be achieved with both methods. However, both methods require some decisions to be made by the researcher during the course of the analysis.

In modelling time series of adverse health outcomes and air pollution exposure, it is important to model the strong temporal trends present in the data due to seasonality, influenza, weather and calendar events. Recently, rigorous statistical time series modelling approaches have been used to better control for these potential confounders. Furthermore, sophisticated analytical techniques have been introduced to adjust for seasonal trends in the data, culminating in the introduction of the generalized additive model (GAM). Although temporal trends can be explicitly included in the model, nonparametric local smoothing methods (LOESS) based on the GAM were widely used to take into account such trends in the analysis. Dominici et al. (2002b) suggested another approach using parametric natural cubic splines in the GAM model instead of the LOESS. One of the main limitations of this type of time series modelling approach is that it is necessary to choose the time span in the LOESS smoothing process, or the degrees of freedom of the cubic splines, and the results can be very sensitive to how that is done.

The case-crossover design compares exposures at the time of the event (i.e. hospital admission) with one or more periods when the event is not triggered. Cases serve as their own controls. The excess risk is then evaluated using a pair-matched design and conditional logistic regression analysis. Proper selection of referents is crucial with air pollution exposures, because of the seasonality and long term time trend. Careful referent selection is important to control for time-varying confounders, and to ensure that the distribution of exposure is constant across referent times, which is the main assumption of this method. Distinct from confounding there is another concern regarding time trend in the exposure series. If there is a long-term time trend, choosing referents only prior to the index day may lead to bias. Different strategies, such as bidirectional referent selection (choosing referents both before and after the index time) (Navidi, 1998) have been proposed to reduce the bias.

3.1 Uncertainty in the risk assessment

For any risk assessment conducted based on a Poisson time series or a case-crossover design is important to verify the model assumptions and to evaluate the model performance. Thus, there is need to assess the performance of the different variations of time series and case-crossover procedures to establish associations between air pollution and human health. Sensitivity analysis of the time series procedure to the statistical representation of the confounding effects need to be conducted. In particular, the sensitivity of the results with respect to the co-pollutants introduced in the model, the time span used in the LOESS smoothing process, and to the degrees of freedom when choosing cubic splines need to be determined. For the case-crossover studies using bi-directional control selection, sensitivity analysis regarding the choice of time interval need to be conducted.

4 Estimation of the C-R function

Short-term health impact indicators can be calculated using concentration-response (C-R) functions. A C-R function summarizes the associations between various measures of air pollution and the health outcome. Questions remain about the shape of those associations. Local C-R functions can be obtained from case-crossover or time series analysis using local information. However, since there is usually limited data for each location, pooling information across similar regions may improve local C-R estimates. A local analysis ignores information from other locations/periods, and could result in a less accurate estimate of the C-R local function. There is a precedent for use of methods that combine a local C-R function analysis with C-R functions from other locations and times, for example, Post et al. 2001, Trete et al., 2005, Dominici et al. 2002a, and Fuentes et al. 2006. We discuss in this section these different approaches to estimate local C-R functions. We start with simple local regression approaches, then we introduce external C-R functions, the next approach would be the use of shrunken estimates (empirical Bayes) and finally the use of Full Bayesian approaches. The degree of statistical training and the computational challenges increase as move along this list from the local regression to the Bayesian approaches. While Bayesian approaches are recommended because they characterize better different sources of uncertainty, depending on the resources one would have to make a decision about what method to use. The purpose of this Section is to highlight the advantages and limitations of each approach.

The C-R function assumed in most epidemiological studies on health effects of particulate matter (PM), ozone and other ambient pollutants, is exponential: $y = Be^{\beta x}$, where x is the exposure level, y is the incidence of mortality (or other adverse health outcome) at level x, β is the coefficient of the environmental stressor, and B is the incidence at $x = 0$ when there is no exposure). In these epidemiological models at the local or state level, we assume that the counts of the health outcome come from a Poisson process. Thus, we have,

$$\ln(E(y_t^c)) = \beta^c P_t^c + \eta^c X_t^c \tag{1}$$

where $E(y_t^c)$ represents the mean counts of the health outcome in the subdomain c on day t, P_t^c are the daily levels of the environmental stressors at location c and day t, β^c is the parameter to be estimated, which is the coefficient multiplying the environmental stressor. The log relative risk (RR) parameter is usually defined as $\beta^c * 10^3$. X_c^t is the vector of the confounding factors (e.g. seasonality, weather variables, influenza and calendar events) and η^c is the corresponding vector of coefficients. The confounder term in this model is often replaced with a smooth function of the covariates (e.g. splines).

Local estimates

Local estimates of β^c can be obtained at each location c separately, using a regression technique applied to model (1). Local regression would allow for more local covariate control. However, the evidence across different locations is ignored.

Adjusted estimates (external C-R function)

Local estimates can be combined using a random effects model, by regressing the local estimates against potential effect modifiers. The model assumptions are:

$$\hat{\beta}^c \sim N(\mu^c, S_{W,c}^2),$$

$$\mu^c \sim N(\alpha Z^c, \sigma_B^2).$$

If we ignore the potential variability within location c of the effect modifiers αZ^c, we have

$$\hat{\beta}^c \sim N(\alpha Z^c, S_{W,c}^2 + \sigma_B^2)$$

$\hat{\beta}^c$ is the estimated effect of P in location c, $S_{W,c}^2$ is the estimated within location c variance, and σ_B^2, is the between locations variance. $\hat{\beta}^c$ and $S_{W,c}^2$ are obtained from the local regression analysis. The between locations variance, σ_B^2, is usually estimated with the maximum likelihood estimate, using an iterative approach.

The random-effects pooled estimate is a weighted average of the location-specific $\hat{\beta}^c$. The weights involve both the sampling error (the within-location variability) and the estimate of σ_B^2, the variance of the underlying distribution of μ^c (the between-location variability).

Shrunken estimates

An alternative to the local estimates and to the overall (pooled random effects) estimate is obtained using the local shrunken estimates. The model assumptions are:

$$\hat{\beta}^c \sim N(\mu^c, S_{W,c}^2)$$

$$\mu^c \sim N(\tilde{\beta}, \sigma_B^2) \tag{2}$$

where $S_{W,c}^2$ is the estimated within-location variance and obtained in a first-stage local analysis as the squared standard error (SE) from the local regression model, $\hat{\beta}^c$ is the Maximum likelihood (ML) estimate from the local regression. $\tilde{\beta}$ is the overall pooled estimate, and σ_B^2 is the between-location variance (treated as known, and obtained in a first-stage analysis using a maximum-likelihood approach).

Then, we can obtain the following conditional distribution:

$$\mu^c | \hat{\beta}^c, \tilde{\beta}, S_{W,c}^2, \sigma_B^2 \sim N(\frac{S_{W,c}^2}{S_{W,c}^2 + \sigma_B^2}\tilde{\beta} + \frac{\sigma_B^2}{S_{W,c}^2 + \sigma_B^2}\hat{\beta}^c, \frac{S_{W,c}^2 \sigma_B^2}{S_{W,c}^2 + \sigma_B^2}),$$

this is called the posterior probability distribution of μ^c. The mean of this posterior distribution is also called the *shrunken estimate* of β^c. The variance of the shrunken estimate is $\frac{S_{W,c}^2 \sigma_B^2}{S_{W,c}^2 + \sigma_B^2}$, which is clearly smaller than $S_{W,c}^2$, the variance of our local regression estimate, because by introducing the spatial information we are able to reduce the variability of our risk estimate. This shrunken estimate includes information from the overall and the local estimates, and thus it characterizes the estimated excess of risk due to heterogeneity between the different locations. In the presence of heterogeneity, location-specific estimates vary regarding the overall effect estimate for two reasons: a) the true heterogeneity in the estimates, and b) additional stochastic error. A location-specific estimate reflects the first source of variation but not the second one. The use of shrunken estimates allows reduction of the stochastic variability of the local estimates. This shrunken method is an *empiri-*

cal Bayesian method, because $\hat{\beta}^c$, $\tilde{\beta}$, and the within and between variance parameters, are treated as known, and therefore the uncertainty about these parameters is not taken into account in the analysis. This could lead to underestimation of the variance associated to the log relative risk parameter.

Effect modifiers (external C-R function), αZ^c, could be also easily introduced in this empirical Bayes framework, by replacing in our model $\tilde{\beta}$ with αZ^c.

Full Bayesian approach

A full Bayesian approach is an extension of the shrunken method, to characterize the uncertainty in the pooled estimate, $\tilde{\beta}$, and the within location estimate, $\hat{\beta}^c$, when obtaining the final estimate of the effect of the environmental stressor at a given location. Thus, rather than treating $\tilde{\beta}$ and σ_B^2 as known, they are modelled as random effects that are jointly estimated at all locations. This would just a one way random effects model which is easy to fit.

A Bayesian multi-stage framework would allow to characterize the spatial dependency structure of the relative risk parameter, by treating β_c as a spatial stochastic process (Fuentes et al, 2006). Lee and Shaddick (2007) smoothed the risk across time. However, this spatial/temporal analysis is usually highly dimensional, and the computational demand of a full Bayesian approach can be extremely laborious. The computation is often simplified by using empirical Bayes alternatives, such as the shrunken estimate.

5 Uncertainty in the C-R function

Concentration-response functions, established by the epidemiological models, play a crucial role in the estimation of the risk associated to different pollutants. Uncertainty in the C-R function may impact conclusions. As described in the previous section, some of the formal approaches for uncertainty analysis in epidemiological models, include Bayesian analysis and Monte Carlo analysis.

To deal with epidemiological model uncertainty, it is possible to compare alternative models, but not combine them, weight predictions of alternative models (e.g. probability trees), and/or the use meta-models that degenerate into alternative models. For comparison of different models to estimate the C-R function, we recommend to use statistical information criteria, that have traditionally played an important role in model selection. The basic principle of model selection using information criteria is to select statistical models that simplify the description of the data and model. Specifically, information methods emphasize minimizing the amount of information required to express the data and the model. This results in the selection of models that are the most parsimonious or efficient representations of observed phenomena. Some of the commonly used information criteria are: AIC (Akaike information criterion, Akaike, 1973, 1978), BIC (Bayesian information criterion, also known as the Schwarz criterion, Schwarz, 1978), RIC (Risk inflation criterion, Foster and George, 1994), deviance information criterion (DIC), which is a generalization of the AIC and BIC. The DIC is particularly useful in Bayesian model selection problems where the posterior distributions of the models have been obtained by Markov chain Monte Carlo (MCMC) simulation. These criteria allow to describe the level of uncertainty due to model selection, and can be used to combine inferences by averaging over a wider class of models (meta-analysis) using readily available summary statistics from standard model fitting programs.

Sensitivity analyses need to be conducted to understand the sensitivity of results to the assumed shape of the concentration-response function and to other model assumptions; in particular to the role of confounders, demographic factors, co-pollutants, the structure of the cessation lag, and sensitivity of the premature mortality estimate (or other endpoints) to the presence of a potential threshold.

There are also uncertainties associated with the environmental stressor, and reliability of the limited ambient monitoring data in reflecting actual exposures (as discussed in the exposure assessment section). These uncertainties would propagate to the epidemiological model, so it is important a good characterization of uncertainties in the exposure assessment. The ability to quantify and propagate uncertainty is still an area in development. Using a hierarchical framework would help quantify uncertainties, the fitting can be done stage-by-stage, taking the interim posteriors from one stage as the priors for the next. Within each stage a fully Bayesian approach can be used to get the interim posterior distributions. As the implementation is based on the sequential version of the Bayes theorem, the corresponding model uncertainties will be captured at the final stage of the hierarchical model. The HB-PHASE framework to obtain exposures fits naturally within this multi-stage approach, by treating the exposure distributions obtained from the HB approach as priors in the next stage, in which we estimate the RR. However, this can be computationally demanding. Uncertainty analysis has certainly developed further and faster than our ability to use the tools in decision-making. Effective uncertainty communication requires a high level of interaction with the relevant decision makers to ensure that they have the necessary information about the nature and sources of uncertainty and their consequences.

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ANNEX B2.

Hubbell B, Fann N, Levy JI. Methodological Considerations in Developing Local Scale Health Impact Assessments: Balancing National, Regional, and Local Data.

ANNEX B

Methodological Considerations in Developing Local Scale Health Impact Assessments: Balancing National, Regional, and Local Data

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I. Introduction

One of the principal objectives of a local scale health impact assessment is to provide a highly resolved estimate of the magnitude and spatial heterogeneity of the health impacts expected to occur as a result of air quality changes at a local level. This type of assessment utilizes many of the same methods applied to the traditional national scale analysis and adapts them for the local area of interest. Such an assessment is clearly of significant analytical value. However, moving from the national to the local scale poses special challenges. Namely, the input data for the local assessment must be highly refined. Local scale assessments also entail unique uncertainties. This paper explores these methodological issues by detailing both the data requirements for performing a local-scale assessment compared to the traditional national assessment and the tradeoffs that analysts must weigh when performing local scale assessments.

In contrast with local scale assessments, there is an extensive history of national health benefits assessments of major air pollution regulations in the United States. For example, the U.S. Environmental Protection Agency (EPA) has regularly performed national scale benefits assessments. In one such analysis it estimated that implementation of the Clean Air Act amendments would result in approximately 23,000 premature deaths avoided in 2010, relative to a baseline of Clean Air Act implementation without the amendments (U.S. EPA, 1999). More recently, EPA has systematized this approach by developing the Environmental Benefits Mapping and Analysis Program (BenMAP) for estimating national health benefits. BenMAP was used in recent Regulatory Impact Analyses (RIAs) of the Clean Air Interstate Rule and Nonroad Diesel Rule (U.S. EPA, 2004, 2005), finding that, when fully implemented, those two rules alone would result in close to 30,000 premature deaths from air pollution avoided annually. The general approach utilized within these analyses has been found to be reasonable and informative for policy decision-making in spite of inherent uncertainties (NRC, 2002).

In recent years, interest has grown in developing similar types of health impact analyses at a sub-national or local level (considered herein to be city-scale). For example, multiple studies have quantified the public health benefits associated with pollution controls at specific power plants, including detailed characterization of the spatial patterns of benefits (Levy et al., 1999; Levy and Spengler, 2002; Levy et al., 2002a). BenMAP analyses have been conducted to address a variety of risk management questions in Philadelphia, Detroit, California, Georgia, Minnesota, and for the Lake Michigan Air Directors Consortium (LADCO)[1]. The spatial distribution of demographic characteristics of the population, the estimated population exposure patterns, and disease patterns —all key inputs to the benefits assessment— may vary significantly within a given urban area. In general, as the spatial scale decreases, national or "generic" data may become less representative, but at the same time, local data may not be available or may be more uncertain given smaller sample sizes.

The decision to pursue a local scale health impact assessment rather than a national scale assessment is clearly linked to the policy objective, but the reliability and interpretability of a local

[1] A list of links to these local scale analyses is provided at the end of this paper.

analysis depend on a number of analytical inputs. As we detail in this paper, a defensible local health impact assessment requires robust and representative data on air quality, populations, baseline incidence rates of health outcomes of interest, and concentration-response relationships relating exposure and health outcomes (Figure 1). In addition, there is a tension between developing assessments that are locally meaningful and using methods that are consistent with other health impact assessments, so that results can be compared across settings. Finally, if health impact assessments are to be conducted on a regular basis, the health impact assessment methodology should provide a mechanism for collection and use of regularly updated data and concentration-response functions.

This paper explores each of these issues in depth. In section 2, we provide a brief conceptual overview of national health impact assessment methods. In section 3, we discuss critical data issues that must be addressed when scaling health impact assessments down from the national to local level. In section 4, we discuss the need to consider the influence of time-varying factors in developing and applying impact functions across multiple years in a local assessment. In section 5, we discuss characterization of uncertainty. Finally, in section 6, we conclude with some recommendations for the conduct of local scale health impact assessments.

II. Overview of national scale health impact assessment methods

The key elements of national scale health impact assessments (HIA) are illustrated in Figure 1, and include:

1) Estimate a change in or increment of ambient air quality, using ambient air quality data (from ground-based or satellite measurements), modeled air quality, or a combination of the two.

2) Combine air quality data with population information to determine changes in population-level potential exposure in a form that is relevant given the epidemiological evidence (e.g., the appropriate averaging time).

3) Combine changes in population exposure to ambient air pollution with impact functions[2] to generate distributions of changes in the incidence of health effects. The impact functions are constructed using population data, baseline health effect incidence and prevalence rates, and C-R functions.

4) Characterize the results of the HIA, through the use of summary statistics (e.g. mean, 95 percent confidence interval), graphs (e.g. cumulative distribution functions and box-plots), and maps.

Health impact functions estimate the change in a health endpoint of interest, such as hospital admissions, for a given change in air pollution concentrations (here, considered to be either ambient ozone or particulate matter). A typical health impact function might look like:

[2] The term "impact function" as used here refers to the combination of a) a C-R function obtained from the epidemiological literature, b) the baseline incidence estimate for the health effect of interest in the modeled population, and c) the size of that modeled population. The impact function is distinct from the C-R function, which strictly refers to the estimated equation from the epidemiological study relating the relative risk of the health effect and ambient pollution. We refer to the specific value of the relative risk or estimated coefficients in the epidemiological study as the "effect estimate" or "C-R function". In referencing the functions used to generate changes in incidence of health effects for this paper, we use the term "impact function".

$$\Delta y = y_0 \cdot (e^{\beta \cdot \Delta x} - 1)\,,$$

where y_0 is the baseline incidence (the product of the baseline incidence rate times the potentially affected population), β is the effect estimate (C-R function), and Δx is the estimated change in ambient concentrations. There are other functional forms, but the basic elements remain the same.

Identifying Health Outcomes of Interest

An important initial step in an HIA is to consider which health outcomes to include in the analysis. Several types of data can support this determination, including toxicological studies (animal and cellular studies), human clinical trials, and observational epidemiology studies. All of these data sources provide important contributions to the weight of evidence surrounding a particular health outcome; however, only epidemiology studies provide direct concentration-response relationships which can be used to evaluate population-level impacts of reductions in ambient pollution levels. The selection of a health outcome therefore follows a weight of evidence approach, based on the biological plausibility of effects, availability of C-R functions from well-conducted peer-reviewed epidemiological studies, cohesiveness of results across studies, and a focus on endpoints reflecting public health impacts (like hospital admissions) rather than physiological responses (such as Forced Expiratory Volume in one second (FEV1)). Table 1 lists some of the health endpoints included in recent HIAs for ozone and PM.

The quantitative aspect of HIA therefore relies on the outputs from environmental epidemiology. A downside is that standard epidemiological studies provide only a limited representation of the uncertainty associated with a specific C-R function, measuring only the statistical error in the estimates, usually relating to the power of the underlying study (driven largely by population size and the frequency of the outcome measure). There are other sources of uncertainty in the relationships between ambient pollution and population level health outcomes, including model specification, potential confounding by factors that are both correlated with the health outcome and each other, and many other factors. Other study types may provide insight about these issues but are difficult to capture quantitatively. In recent years, expert elicitation methods have been used to integrate across various sources of data in developing C-R functions for RIAs, a topic discussed in greater detail in Section 5.

Selecting Health Impact Functions

For health outcomes for which multiple studies are available, criteria need to be developed to determine which studies are likely to provide the best estimates of impacts in the U.S., as well as how the estimates from these studies should be weighted and combined. These criteria may include consideration of whether the study was peer-reviewed, the match between the pollutant studied and the pollutant of interest, whether co-pollutant confounding was addressed, the study design and location, and characteristics of the study population, among other considerations. To account for the potential impacts of different health care systems or underlying health status of populations, it may make sense to give preference to U.S. studies over non-U.S. studies, although the relative importance of country-specific information may vary by health outcome (with health care utilization measures likely depending more on country characteristics than disease development).

Table 2 is a summary table from the ozone NAAQS RIA (EPA, 2007) which demonstrates the complexity in the health impact estimates that can result from a national analysis. First, it should be noted that EPA relied on multi-city studies or meta-analyses of the mortality literature, an alternative to selecting individual city estimates, but did not attempt to formally combine the evidence across these studies. The individual row estimates for mortality therefore reflect the variability in the effect estimates for ozone mortality across these studies. Ranges within each column reflect the uncertainty in the ozone effect estimates as well as in the estimates of PM premature mortality impacts across the available effect estimates for PM mortality. Similar characterization could be conducted for morbidity outcomes as well, although the existence of fewer studies makes it more difficult to fully encapsulate uncertainty.

Identifying Baseline Incidence Rates

Given the C-R functions for various health outcomes, the remainder of the impact function depends on baseline incidence and size of the modeled population. Baseline incidence rates are important because the effect estimate calculates a change in the health outcome relative to a baseline incidence rate for the health endpoint of interest. Some epidemiological studies examine the association between pollution levels and adverse health effects in a specific subpopulation, such as asthmatics or diabetics. In these cases, it is necessary to develop not only baseline incidence rates, but also prevalence rates for the defining condition (e.g., asthma). For both baseline incidence and prevalence data, age-specific rates are preferred where available. Impact functions are applied to individual age groups and then summed over the relevant age range to provide an estimate of total population benefits.

Health benefits are calculated by linking the impact function and the modeled changes in air pollution levels. The change in or increment of air quality is generally determined by either a policy scenario (e.g. implementation of SO_2 emission controls at power plants) or a specific standard or target (e.g. reduce $PM_{2.5}$ levels to the annual average standard of 15 $\mu g/m^3$). Air quality changes can be predicted using sophisticated air quality models such as EPA's Community Multiscale Air Quality (CMAQ) model, or more simplified monitor rollback methods can be used to simulate just attaining different standards (see Hubbell, et al., 2005 for an example of the rollback methodology). The appropriate methodology, scale, and resolution of air quality assessment will depend on the problem context.

Characterizing Changes in Incidence

The characterization step includes a number of elements, as described above. One important issue involves whether to characterize mortality impacts as counts of premature deaths avoided (as shown in Table 2) or using other metrics such as life years lost or average life expectancy gained. This latter measure has been used in European assessments, and requires some additional assumptions about the life expectancies of populations affected by PM (Holland and Pye, 2006). Most HIA assume that deaths from PM occur at the same rate (proportional to baseline mortality) across all populations, so that standard life tables available from the Centers for Disease Control can be used to calculate life years lost and changes in life expectancy. EPA provides estimates of life years lost in a separate cost-effectiveness analysis provided as an appendix to their Regulatory Impact Analysis (EPA, 2005; EPA, 2006).

III. Analytical challenges to scaling down HIA from national to local levels

Although health impact assessments are theoretically applicable at sub-national scales, multiple issues arise in developing any of the key inputs to a health impact assessment—the baseline incidence rates, health impact functions, or air quality data. As such, it would be inappropriate to assume that the local scale assessment is simply a more geographically discrete version of the national or regional assessment. Analysts must take special care to recognize how the sources of analytical uncertainty change as the scope shifts from the national to the local scale. The discussion below focuses on each facet of the health impact assessment, describes the tension between national-scale and local-scale data, and discusses how the role of local data in the analysis is affected by the shift in geographic scale.

In general, the tension is captured in the continuum proposed within Figure 3 – in some cases, either limited local data will be available or the data will be less reliable (either because of statistical power issues or other concerns). In those cases, the evidence used in national-scale HIA may be directly applied, with minor modifications and acknowledged uncertainties. Increasing availability of local data may provide refined incidence/prevalence data or insight about factors that could influence the relative risks from air pollution. At the far end of the continuum, sufficient local data may be available to provide site-specific epidemiology and other local data. More detail is provided in the discussion below for each input.

Development of appropriate effect estimates

In most cases, local scale HIAs will need to rely on "off-the-shelf" information available from the epidemiological literature, given either a lack of local studies or the likelihood that such studies would not have adequate statistical power to allow the global literature to be ignored or downweighted. Broadly, there may be data from a sufficient number of cities or studies to be able to determine factors that explain variability in effect estimates across cities, or the literature may be inadequate to do so. In addition, there may be epidemiological studies conducted within the city of interest for the local HIA, or there may be no such studies.

An overarching concern for a local HIA is the transferability of the C-R functions from the context in which they were generated to a specific analytical context. For example, a study relating hospital admissions to ozone concentrations in New York City in 1980 might not be appropriate to directly apply to an analysis of ozone concentrations in Houston in 2007. This is because a number of factors differ between the timeframe and location of the original analysis and the timeframe and location of the new analysis. More specifically, the levels of other pollutants, the nature of the medical systems, population susceptibility to air pollution, population exposure and susceptibility to elevated temperatures, demographics (such as age), and exposure factors such as prevalence of air conditioning may all differ between 1980 New York and 2007 Houston. Careful comparisons of those factors that might change the relationship between ambient pollutant concentrations and health outcomes should be conducted prior to selecting effect estimates for a particular location, as this will help determine whether evidence is applicable directly, applicable with modification, or inapplicable.

When faced with a set of candidate effect estimates from a number of different cities, there are meta-analysis and pooling techniques which can be used to develop effect estimates that reflect potential heterogeneity in C-R functions across cities. Standard meta-analysis or pooling approaches involve weighting candidate studies by (for example) the inverse of their reported variance, providing a central estimate across the literature. An alternative to this approach uses random rather than fixed effects, which allows the possibility that the estimates from the different studies may in fact be estimates of different parameters, rather than just different estimates of a single underlying parameter. While these simple pooling approaches can provide better mean effect estimates for use in national scale analyses, they can lead to biased results when applied to local areas, because some of the variability in effect estimates between locations may be due to systematic factors influencing exposure, susceptibility, or other factors. In this case, more sophisticated meta-analysis approaches may be required.

In recent years, several articles have been published that involve either meta-analyses or new multi-city studies for ozone (Stieb et al., 2002; Bell et al., 2004; Bell et al, 2005; Ito et al, 2005, Levy et al, 2005) and PM mortality (Levy et al., 2000; Stieb et al., 2002; Dominici et al., 2003; Franklin et al., 2007). In addition to developing an overall mean effect estimate, some of these studies attempted to address heterogeneity in effect estimates across cities or studies by determining whether the effect estimates vary as a function of co-pollutant concentrations, temperature, air conditioning prevalence, and other factors. Among other findings, locations with higher air conditioning prevalence appear to have a systematically smaller effect from ozone (Levy et al., 2005) and PM (Franklin et al., 2007). The implication of this for developing effect estimates for specific locations is that national mean estimates may need to be adjusted to account for local factors that are related to the effect estimate, although it should be recognized that the covariates in these meta-regressions may not necessarily be the causal factors driving the C-R functions.

In general, multi-city analyses have some analytical advantages over multi-study meta-analyses, as they impose a consistent model specification, use the same time period for each city included, and are more inclusive of locations, resulting in less chance of any publication bias. However, if the effect estimates are strongly influenced by model specification, single studies may be more likely to be biased than multi-study meta-analyses that may draw on multiple model specifications. Regardless, either type of study can provide city-specific estimates using hierarchical Bayes models, in which individual effect estimates for each city represent priors for those cities, but the posterior estimates represent a weighted average between those observations and the results from a pooling process or meta-regression. If a city-specific estimate is highly uncertain and there is either little heterogeneity in the city-specific estimates or such heterogeneity can be explained by defined characteristics of the cities, then less weight is given to the city-specific observation. In contrast, if there is significant unexplained heterogeneity and the city-specific estimates have good statistical power, then the city-specific estimates are given more weight. This approach recognizes that effect estimates from cities other than the one being evaluated within the HIA provide some insight about the appropriate estimate for the city being evaluated.

Some of the key sources of potential heterogeneity in effect estimates between cities can be divided into two categories: those having to do with differences in exposure, and those having to do with differences in potential susceptibility. Because most epidemiology studies relate health outcomes to central site monitored concentrations rather than personal exposure, factors that affect the relationship between personal exposure and ambient concentrations can potentially affect the C-R function. Some of these exposure-related factors include air conditioning prevalence and utilization, availability and effectiveness of air quality alerts, and amounts of time spent outdoors or in traffic. In addition, differences could be related to the relative levels of ambient pollution (e.g. how much ozone is in the air relative to PM) as well as the composition of PM (e.g. is the mass composed mainly of elemental carbon and sulfates, or is it composed of organics and nitrate?). Other air quality characteristics that may be important include the temporal profiles of pollution (e.g. is the area more affected by peaks or long-term elevated concentrations?).

Other local characteristics that can affect C-R functions include population characteristics. Most epidemiological studies focus on broad population groups. As such, given differences in susceptibility across the population, differences in demographic factors and baseline health across cities can affect estimated C-R functions. Some of these factors that have been identified in the literature include age, prevalence of heart and lung disease, education, income/poverty, access to health care, and asthma prevalence.

In summary, given the likelihood that neither extreme on the continuum in Figure 3 (no relevant local data or substantial and well-powered local epidemiology) will occur, the process for selecting appropriate effect estimates for HIA requires careful development of profiles of characteristics of the city of interest and study locations to find the closest match along a range of attributes that can impact effect estimates. Profiles can be generated using available databases on air quality composition (obtained from the EPA Air Quality System -- http://www.epa.gov/ttn/airs/airsaqs/ or the HEI Air Quality Database -- http://hei.sf.aer.com/login.php), baseline health status (using numerous sources from CDC), demographics (using databases from the U.S. Census Bureau), and other factors such as climate and meteorological variability. Formal matching analyses can be conducted (e.g. clustering of cities based on health and air quality attributes), or less formal approaches based on expert analytical judgment can be used. There is no single rule of thumb on how close areas need to be in attributes space – to some extent this will depend on how much uncertainty is acceptable in the analysis. It will also depend on the attribute. If an attribute has been shown to have a large impact on effect estimates, then the focus should be on matching that attribute as closely as possible. In cases where the information base is more limited, matching may be inapplicable, in which case the analyst should broadly consider the degree of uncertainty and/or bias associated with application of the available effect estimates.

It should be noted that the aforementioned approach is most relevant to time-series studies, which focus on day-to-day variations in pollution within cities. However, another form of study is often used to examine long-term health outcomes associated with chronic exposures. These studies use the variation in long-term pollution concentrations between cities to estimate the C-R function. The best of these studies use prospective cohort designs, which track the survival rates (or disease-free status rates) for individuals over time, and calculate relative risks from pollution controlling for differences in baseline health risks due to smoking status, diet, etc. Because these studies use between-city variability to generate the C-R function, city specific estimates are not available. Thus, when applying the effect estimates from cohort studies, the mean estimate should be used.

However, care should be taken to identify any systematic differences between the populations used in the cohort study and the populations in the location of the HIA. For example, it has been recognized that the population studied in one of the most widely used cohort studies, the American Cancer Society (ACS) Study (Pope et al, 2002), is not representative of the demographic mix in the general population. The ACS cohort is almost entirely white and has higher income and education levels relative to the general population. In EPA's recent expert elicitation study, many of the experts suggested that these sample characteristics led to a downward bias in the estimated C-R functions relative to a C-R function that would be representative of the general U.S. population (Roman et al, 2008).

Most previous HIA (EPA, 2005; EPA, 2006; Levy and Spengler, 2002; Levy et al., 2002a) have used estimates from the Harvard Six Cities (Laden et al, 2006) and ACS (Pope et al, 2002) studies of PM related mortality, given concerns that other published cohort studies do not match the national population in terms of demographics, risk factors, or disease status. For example, the Washington University-EPRI Veterans Cohort Study (Lipfert et al., 2006) involved male hypertensive veterans receiving treatment at VA clinics, with 57% current smokers (versus 24% in the general population). Another cohort study (McDonnell et al., 2000) focused only on non-smoking Seventh-Day Adventists in California. In either case, the populations differed in multiple ways that could significantly impact the effect estimates. As it is unlikely that any general population HIA will exclusively capture such targeted populations, even at a local scale, the Six Cities and ACS study estimates will be more relevant for local HIA.

Baseline incidence/prevalence data

Unlike with effect estimates, it is likely that substantial local baseline incidence/prevalence data could be available for at least some health outcomes, putting this step of the HIA further along the continuum in Figure 3. First, as a general point, the way in which the health outcome is defined should be in agreement with the epidemiological studies underlying the effect estimates, and the spatial resolution and scale of the baseline incidence or prevalence rate should ideally match the resolution of the HIA.

For many health outcomes, utilizing baseline incidence data that are not specific to a given location or that are not adequately geographically resolved can introduce important uncertainties to the analysis. For example, in Boston, premature mortality rates (Chen et al., 2006) and asthma hospitalization rates (Gottlieb et al., 1995) have been shown to differ substantially by neighborhood, depending in part on socioeconomic status. As another example, as shown in Figure 4, zip-code level asthma hospitalization rates vary substantially within Detroit, ranging from a maximum of 129 to a minimum of 10 per 10,000. This range is significantly different than the single national estimate of 28 in 10,000 that EPA applies in its regulatory analyses (EPA, 2005; EPA, 2006).

The policy implications of using alternate baseline incidence rates become clear when estimating the total changes in asthma-related hospital admissions resulting from changes in $PM_{2.5}$ levels. For example, using the EPA default baseline hospitalization rate generates a total reduction in asthma-related hospitalizations of 36 cases (90^{th} percentile confidence interval from 17 to 54). In contrast, using the local-scale rates produces a reduction in asthma-related hospitalizations of 53 cases (90^{th} percentile confidence interval from 26 to 81). Clearly, using national-scale baseline incidence rates would under-estimate the total change in this particular health endpoint in Detroit, and would not capture the spatial and demographic variability in that endpoint. Similar differences in the results of local-scale HIA have been observed when using geographically-averaged baseline rates versus demographically-stratified rates that vary by location (Levy et al., 2002a).

The chief impediment to using such high resolution baseline incidence data is that it is very resource-intensive to produce or it may simply not be available for the outcome of interest. For example, while the Wayne County Department of Public Health maintains a comprehensive asthma epidemiology database, it was necessary for an epidemiologist to reformat these data to generate tables in a format suitable for use in a health impact assessment. Moreover, neither the County nor the State Department of Public Health was able to provide refined estimates of baseline incidence rates for other important health $PM_{2.5}$ endpoints, such as non-fatal heart attacks or chronic bronchitis.

Given these constraints, local scale baseline incidence rates for each health endpoint of concern will not always be available. However, rather than relying solely on national or broad regional estimates, it may be possible to apply interpolation or other estimation techniques to infer the baseline rates for the city of interest. For example, if incidence rates correlate well with some number of easily observed independent variables—perhaps age, race and geographic region—then one could estimate the baseline incidence rate. This approach has been followed previously, as baseline incidence data were simulated at high resolution for large spatial scales as a function of demographic factors (Levy et al., 2002a). A limitation is the fact that this relies heavily on the assumption that factors such as race and education are universally-applicable causal factors rather than covariates reflecting complex contextual relationships within the underlying studies from which the correlations were developed. Geostatistical interpolation techniques, such as kriging and co-kriging, may also be of some use in creating a spatial surface of interpolated baseline incidence rates. The uncertainty these methods introduce, though significant, is likely outweighed by the improved representation of geographic heterogeneity inherent in baseline incidence rates.

Air quality data

Changes in air quality—monitored or modeled—ultimately drive estimates of health impacts. A key analytical challenge is to represent both the spatial distribution and scale of these air quality changes. For pollutants such as $PM_{2.5}$, we would expect a high degree of variability in the geographic distribution of air quality changes across urban areas, given certain source controls, while at the same time long-range transport may affect populations located outside of the urban area. For example, evidence suggests that directly-emitted carbonaceous particles from motor vehicles are subject to a steep spatial gradient as a function of distance from the roadway (Zhou and Levy, 2007). By contrast, other studies have shown that health impacts need to be characterized at a regional or national scale, especially for point sources and secondarily-formed particulate matter (Greco et al., 2007; Levy et al., 2002b; Levy et al., 2003).

Without knowing the policy context for the HIA, it is therefore difficult to know the extent to which monitors or models can be used, or the necessary scale and resolution. One general statement that can be made is that the exposure data must be reasonably in agreement with the way in which exposure was characterized within the underlying epidemiological studies. If the concentration-response function is derived from a single central-site monitor, highly spatially-resolved exposure characterization would be difficult to interpret within an HIA. That being said, finer-scale air quality data will clearly take on added importance for a local HIA, in which it may be of interest to align inputs such as the baseline incidence rates and populations with the spatial air quality gradient.

Comparing locally developed health impact estimates with literature-based estimates

In many cases, even if analysts conduct an HIA using locally generated baseline incidence and prevalence data, C-R functions, and air quality data, it may be useful to generate health impacts using literature based estimates as well as a way of putting the local data-based estimates into context. In comparing estimates generated using national and local data, it will be important to understand what differences might be expected versus differences that cannot be expected or explained. In addition to evaluating differences between attributes of locations, analysts should also be aware of the timeframe in which a national analysis was conducted. Some population or air quality characteristics may have changed significantly between the time when a study was conducted and the present, as discussed in more detail below.

In addition to local area attributes, analysts should also compare the statistical methodologies used in generating the local area estimates relative to those used in generating the national estimates. For example, if different functional forms are used for a local epidemiological study and the published literature (e.g. two-day moving average vs. distributed lags), then there may be differences in the expected results, solely from the statistical methods used. Similarly, data collection and aggregation methods may differ for baseline incidence/prevalence data.

IV. Consideration of time-varying factors in developing and applying impact functions across multiple years

As noted above, changes over time in local level attributes that affect air quality, populations, and population exposures can make comparison of local health impact estimates over time challenging. From an accountability perspective, if these changes are not accounted for, then the "signal" from programs intended to reduced air pollution related health risks can be masked or overstated. For example, if the age composition of a population is becoming older over time, but age is not incorporated into a time series design, then relative risks to a population may appear to increase over time, even as pollution levels decrease, simply because the "at risk" susceptible proportion of the population is increasing.

Some time-varying factors that should be considered when designing a multiple year assessment program include demographics, exposure modifiers, air pollution sources, pollutant composition, and meteorology/climate. Demographic factors may include age composition, race, educational levels, income and income disparity, and population health characteristics such as rates of obesity, asthma, and heart disease. This essentially includes covariates that could explain between-site variability in effect estimates or baseline incidence rates, so the process of determining the appropriate impact functions for a local HIA can help to elucidate the most significant time-varying factors to consider. Some recent evidence also suggests that it is important to account for public health interventions that might modify the impacts of air pollution on health. For example, a recent study by Schwartz et al. (2005) found that the introduction of statin drugs reduces the relative risk from PM. The widespread and increasing use of statin drugs in the population may then affect the observed relative risks from PM over time.

Changes in the composition of air pollution may occur both due to pollution control programs and due to natural economic factors such as plant closures. Pollution control programs may target one pollutant over another, e.g. reducing SO_2 while leaving direct carbon levels unaffected, or may even decrease one pollutant while increasing another, e.g. adding catalytic converters to cars reduces NOx emissions but increases NH_3 emissions.

Finally, as climate changes over time, both the susceptibility of populations to air pollution and the nature of air pollution events may change. Higher temperatures may increase susceptibility to air pollution related health effects (Roberts, 2004). Several recent studies have found an increased risk of air pollution stagnation events under projected changes in the global and regional climate, which are expected to decrease the cyclone frequencies (Leung and Gustafson, 2005; Mickley et al, 2005; Wu et al, 2007)

Forward looking design of health impact assessment protocols can help to avoid comparability problems by including controls for time-varying factors. With the proper study design, as conditions change, the changes in effects expected from air pollution reductions can be isolated from changes in effects due to other time-varying factors.

V. Characterizing uncertainty in health impact estimates

An important component of any local or national HIA is a characterization of the uncertainties associated with estimates of health impacts. While techniques exist to provide probabilistic estimates of impacts, those techniques are limited by a lack of input data on uncertainty in individual impact function elements. For some elements, such as the effect estimate, there is at least some limited information on uncertainty, in the form of standard errors from the statistical estimation, while for others, e.g. baseline incidence rates, there is no information available.

Bayesian approaches, such as hierarchical Bayes analyses used in multicity studies, can provide additional characterization of uncertainty, because they partially account for heterogeneity between cities, thus accounting for some of the uncertainty about transferability. However, even these approaches cannot address overall model uncertainty or uncertainty about causality.

As alluded to earlier, one approach that has been utilized in a limited number of settings involves formal expert elicitation. The U.S. EPA recently conducted an expert elicitation to try to provide a more complete assessment of the uncertainties associated with the effect estimate for PM related mortality (Roman et al., 2008). The process and results for this study are available at http://www.epa.gov/ttn/ecas/regdata/Uncertainty/pm_ee_report.pdf . Expert elicitation is useful in integrating the many sources of information about uncertainty in the C-R function, because it allows experts to synthesize these data sources using their own mental models, and provide a probabilistic representation of their synthesis of the data in the form of a probability distribution of the C-R function. The goal of the study was to elicit from a sample of health experts probabilistic distributions describing uncertainty in estimates of the reduction in mortality among the adult U.S. population resulting from reductions in ambient annual average $PM_{2.5}$ levels. The main quantitative question in the formal interview protocol asked experts to provide the 5th, 25th, 50th, 75th, and 95th percentiles of a probabilistic distribution for the percent change in U.S. annual, adult all-cause mortality resulting from a 1 $\mu g/m^3$ change in annual average $PM_{2.5}$ exposure, assuming a range of baseline $PM_{2.5}$ levels between 4 and 30 $\mu g/m^3$. Expert elicitation methods are still somewhat controversial, and care should be taken to follow formal expert elicitation protocols. It is also unlikely that expert elicitations at this scale would be conducted for an individual local HIA, or even for many of the key elements, given the cost, time, and a lack of empirical data from which experts could derive informed opinions. However, results from available expert elicitations can provide a more robust understanding of uncertainties in different analytical components, and may eventually provide insight about some of the transferability concerns central in local HIA.

In addition to formal probabilistic analyses, sensitivity analyses are also a useful way to understand how sensitive results are to alternative assumptions. Sensitivity analyses can be used to examine individual assumptions or combinations of assumptions. When communicating the results of sensitivity analyses, care should be taken to indicate the potential likelihood of the set of assumptions to avoid giving an artificially distorted impression of the likely range of impacts.

There are some types of uncertainties that are especially important when conducting a local scale analysis using national level data or transferring data from a different location. These uncertainties relate to the factors identified in the sections above on choosing effect estimates. These uncertainties can be minimized by careful selection of effect estimates based on cities that are similar to the city under analysis. Other sources of uncertainty at the local level include uncertainty in the application of regional or national baseline incidence rates and uncertainty in air quality levels assigned to specific populations. These uncertainties can be minimized by using as spatially refined estimates as available.

VI. Conclusions and recommendations

Properly conducted local health impact assessments can be informative and defensible. However, there are many opportunities for biases and uncertainties to be introduced into the analytical process. Careful attention to the inputs to the analysis can help to minimize uncertainties and reduce the potential for biased results. In addition, comparison with results from other locations or with national results can provide context for the results and a check on the reasonableness of estimates.

Some key recommendations for conducting interpretable local HIA include:

- Clearly identify characteristics of study locations that may influence health effect estimates, including air quality composition, population demographics (age, race, income, etc.), and climate/meteorology. When applying previously-published studies, pay attention to statistical designs, including functional forms, controls for weather and other confounders, lag structures, and treatment of missing values, and timeframes for each study from which an effect estimate is derived.
- Compare characteristics in the local area to the characteristics of the source study locations and select effect estimates from studies or cities with characteristics closely matching those of the local area.
- Choose a spatial resolution for air quality data appropriate given the exposure assessment within the epidemiological studies of interest, the spatial gradient in air pollution given the pollutant and sources being controlled within the assessment, and potential for correlation with population demographics. In cases where there is a sharp gradient in air pollution that is highly correlated with spatial gradients in population density or susceptibility characteristics, high resolution data should be used in spite of the attendant uncertainties and potential issues in combining these data with epidemiological evidence based on central-site monitors.
- Baseline health outcome data should be as spatially and demographically refined as possible. When local baseline health data are not available, analysts should consider using prediction or interpolation methods to derive local baseline rates using national or regional estimates coupled with locally available data shown to be correlated with the health outcomes of interest.
- Design multi-year studies with accountability and comparability in mind. Designs should incorporate time-varying factors, including baseline population health (which may be influenced by the availability of certain types of medical interventions like prevalence of statin drug use), socioeconomic factors, climate (e.g. mean summer temperatures), sources of emissions (which can affect the composition of local air pollution), and availability of detailed air quality forecasts, that can influence the relationship between air pollution and health.
- Uncertainty should be discussed and characterized quantitatively where possible. Probabilistic approaches can be used to characterize some uncertainties, but should be accompanied by single and multi-attribute sensitivity analyses to address uncertainties that do not have good probabilistic data available.

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Links to Recent Local Scale BenMAP Applications:

1. Georgia (Cohan, Daniel S., James W. Boylan, Amit Marmur and Maudood N. Khan. 2007. An Integrated Framework for Multipollutant Air Quality Management and Its Application in Georgia. Environmental Management, 40(4): 545-554)
2. Philadelphia (http://www.cleanair.org/dieseldifference/resources/reports/pmphillyreport.html)
3. Detroit (http://www.cleanairinfo.com/regionalstatelocalmodelingworkshop/old/2007/presentations/Thursday%20-%20May%2017%202007/Air_Toxics_Update_Detroit_Study.pdf)
4. Baltimore (???)
5. LADCO (Deck, L. 2006. Benefit Study of MRPO Candidate Control Options for Electricity Generation. Stratus Consulting Inc. Prepared for: Lake Michigan Air Directors Consortium, available at http://64.27.125.175/reports/rpo/Regional%20Air%20Quality/EGU%20Benefit-Cost%20analysis%20Stratus.pdf)
6. Minnesota (ICF Consulting, 2005. Air Quality and Health Benefits Modeling: Relative Benefits Derived from Operation of the MEP-I/II IGCC Power Station. Prepared for Excelsior Energy Inc. Available at http://www.excelsiorenergy.com/pdf/Regulatory_Filings/Docket_E6472_M-05-1993/20051227InitialFiling/15%20Exhibit%20D.pdf)
7. California (Chang, E., L.T. Tsiopulos, and. J. Whynot. 2007. Final Socioeconomic Report for the 2007 AQMP. South Coast Air Quality Management District. Available at: http://www.aqmd.gov/aqmp/07aqmp/07AQMP_socio.html)

ANNEX B

Table 1. Health Endpoints Included in Recent U.S. EPA National Health Impact Assessments (EPA, 2005; EPA, 2006).

Health Endpoint	PM	Ozone
Mortality	✓	✓
Chronic bronchitis	✓	
Nonfatal heart attacks	✓	
Hospital admissions	✓	✓
Asthma ER visits	✓	✓
Minor Restricted Activity Days	✓	✓
Asthma attacks	✓	✓
Work loss days	✓	
Worker productivity		✓
School absence rates		✓

Table 2. Summary of 2020 National Health Impacts Associated with Attainment Strategies for Alternative Ozone NAAQS (EPA, 2007).

Combined Estimate of Mortality *Standard Alternative and Model or Assumption*[A]		*Combined Range of Ozone Benefits and $PM_{2.5}$ Co-Benefits*			
		0.079 ppm	0.075 ppm	0.070 ppm	0.065 ppm
NMMAPS	Bell (2004)	200 to 1,900	430 to 2,600	670 to 4,300	1,200 to 7,400
	Bell (2005)	260 to 2,000	1,100 to 3,300	1,500 to 5,100	2,800 to 9,000
Meta-Analysis	Ito (2005)	270 to 2,000	1,200 to 3,300	1,600 to 5,200	3,000 to 9,200
	Levy (2005)	260 to 2,000	1,300 to 3,500	1,800 to 5,400	3,000 to 9,200
No Causality		180 to 1,900	230 to 2,400	390 to 4,000	660 to 6,900
Combined Estimate of Morbidity					
Acute Myocardial Infarction		1,100	1,400	2,300	4,000
Hospital and ER Visits		1,300	5,600	7,600	13,000
Chronic Bronchitis		370	470	780	1,300
Acute Bronchitis		950	1,200	2,000	3,500
Asthma Exacerbation		7,300	9,400	16,000	27,000
Lower Respiratory Symptoms		8,100	10,000	17,000	29,000
Upper Respiratory Symptoms		5,900	7,500	13,000	22,000
School Loss Days		50,000	610,000	780,000	1,300,000
Work Loss Days		51,000	65,000	110,000	190,000
Minor Restricted Activity Days		430,000	2,000,000	2,700,000	4,700,000

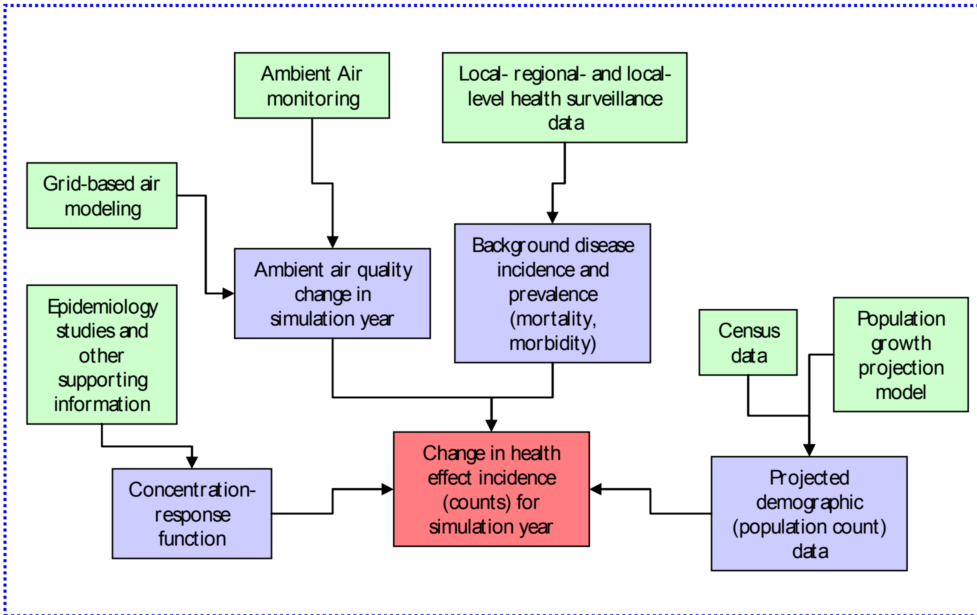
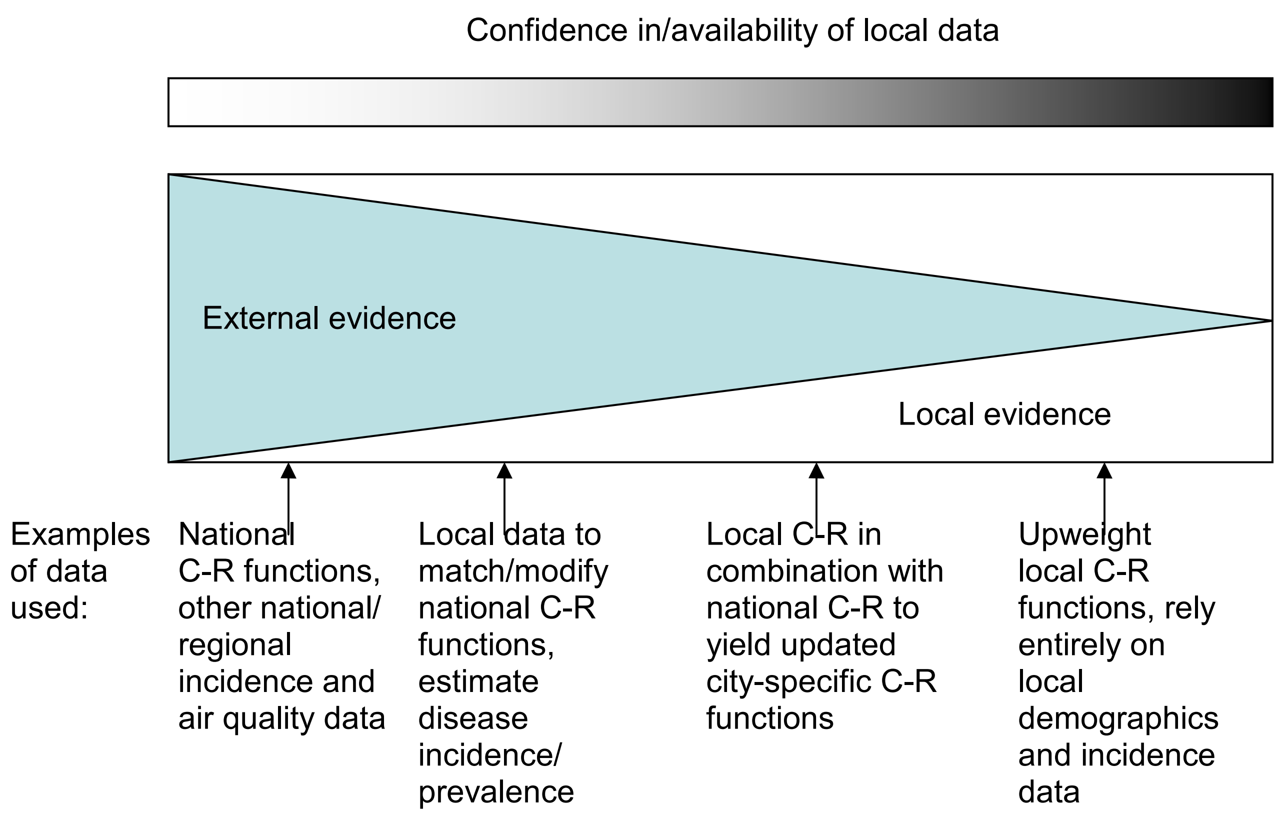


Figure 1. Health Impact Assessment – Analytical Framework

ANNEX B

Figure 2. Continuum for use of national vs. local data in local scale health impact assessments. Note that a separate continuum would be applicable for each health outcome.



ANNEX B

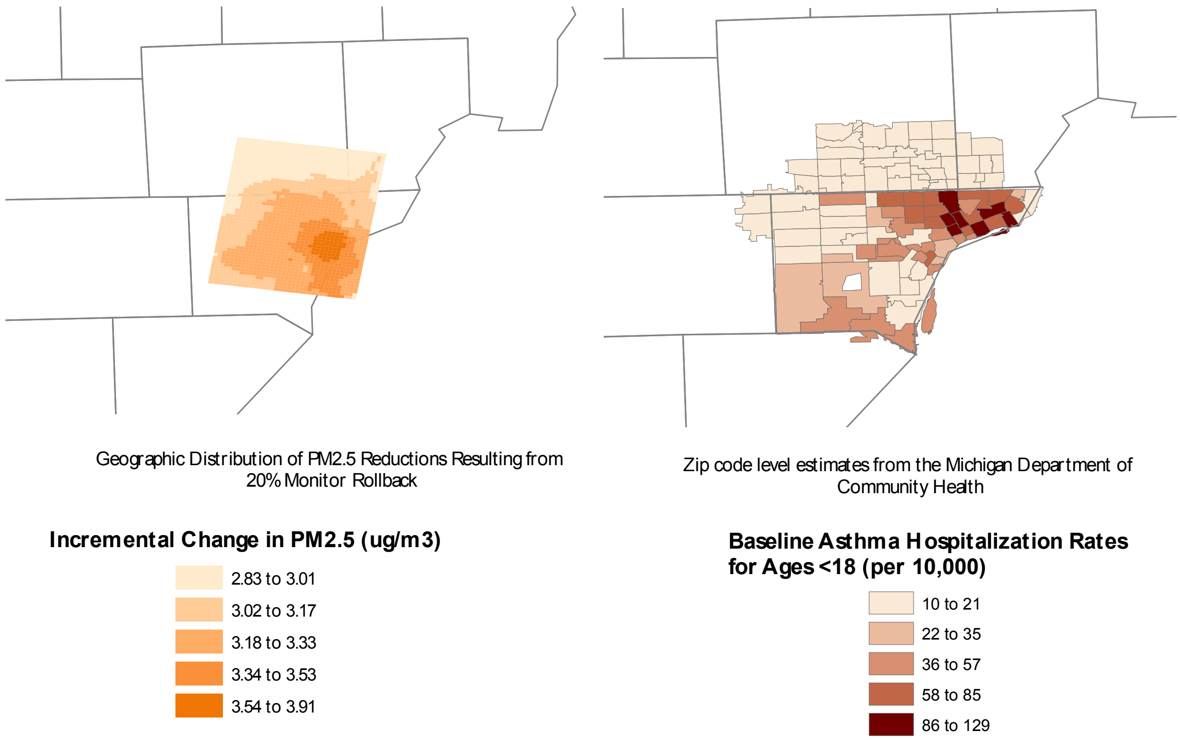


Figure 4. Comparison of the Geographic Distribution of Zip-Code Level Asthma Hospitalization Rates and a Hypothetical 20% Reduction in Monitored $PM_{2.5}$ in the Detroit Metropolitan Area

ANNEX B3.

White W. Considerations in the use of ozone and $PM_{2.5}$ data in exposure assessment.

ANNEX B

Considerations in the use of ozone and $PM_{2.5}$ data in exposure assessment

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Workshop on Methodologies for Environmental Public Health Tracking (EPHT) of Air Pollution Effects, Baltimore 1/15-16/08

Ozone and $PM_{2.5}$ as air quality indicators

Ambient air is a complex mixture of gases and suspended particles. EPHT will focus on ozone and $PM_{2.5}$, which have demonstrated empirical associations with public health statistics. These two indicators do not characterize all potential dimensions of toxicity, and their relationships to other species will merit consideration when interpreting EPHT results. We begin with some background on these relationships.

Ozone concentrations are governed by a system of photochemical reactions involving nitrogen oxides, hydrocarbons, free radicals and other products. These reactions produce relationships among the reactants, an important one being the photostationary state approximated by concentrations of ozone and the nitrogen oxides. The fast cycle, $O_2 + NO_2 + h\nu \rightarrow O_3 + NO$ and $O_3 + NO \rightarrow O_2 + NO_2$, keeps the photostationary ratio $[NO][O_3]/[NO_2]$ near the ratio of the respective rate coefficients. This constraint relates the ozone concentration to the concentrations of nitrogen oxides $[NO_x] = [NO]+[NO_2]$ and odd oxygen $[O_x] = [O_3]+[NO_2]$, which the cycle leaves unchanged. It follows that the near-source effect of NO emissions is to depress ozone concentrations, as evident in Figure 1.

Ozone rises to problem levels through the involvement of radicals and other intermediates formed during oxidation of reactive hydrocarbons. These other species provide alternatives to ozone as pathways for the oxidation of NO to NO_2. Because they do not consume ozone in the process, the slower alternatives allow $[O_x] = [O_3]+[NO_2]$ to accumulate along with other reaction products. Monitoring strategies and exposure metrics for O_3 are designed to capture this accumulation by emphasizing conditions that minimize masking by fresh emissions. Thus health-based air quality standards address the maximum 1h or 8h concentrations recorded anywhere in an area; monitors are set back from roadways, and many operate only during the most photochemically active portion of the year. These choices yield an indication of exposure to the photochemical mix, not just to ozone itself.

$PM_{2.5}$ is defined operationally as the mass of particulate matter (PM) collected on specified filter media under specified conditions, behind a specified inlet designed to exclude particles greater than about 2.5 um in aerodynamic diameter. The collected material is a heterogeneous agglomeration of solid and liquid particles, some of them semi-volatile, that when airborne were of diverse size, shape, and composition (Figure 2). The mass metric "greatly simplifies complex biological phenomena" in the judgment of a recent review (NRC, 2004).

Collected PM can be categorized into components in various ways. It is useful to distinguish between primary particles, which are emitted directly to the atmosphere, and the secondary condensates that atmospheric reactions produce from gaseous emissions. Whereas primary PM concentrations rapidly fall as emissions mix with cleaner background air, secondary PM concentrations may increase for some distance downwind. The primary and secondary components of PM are thus differently distributed even when both arise from the same source of emissions. Chemical composition offers another classification framework, one more directly relevant to toxicity. Coal combustion, which releases both fly ash and sulfur dioxide, provides an illustration of these distinctions. The ash is directly emitted as primary particles whose concentrations peak nearby, while the SO_2 emissions slowly oxidize to form secondary sulfates as they are carried downwind. (Smokestacks of course separate the near-field concentration peaks from ground-level populations.) $PM_{2.5}$ may serve as a reasonable proxy for the sulfate fraction in the eastern U.S., where inorganic sulfates account for much of total $PM_{2.5}$ mass, but is less indicative of fly ash, which is a minor mass contributor. Meanwhile, recent health research has shown more interest in the trace metals carried by fly ash than in sulfates (NRC, 2004).

Concentrations of ozone and $PM_{2.5}$ tend to be more uniform than those of exclusively primary pollutants such as SO_2 and combustion nuclei, which often exhibit "hot spots" near major sources. A multiplicity of emissions contribute to ozone and $PM_{2.5}$, and these are mixed and dispersed in the atmosphere during the time required to form ozone and the secondary species that account for much of the $PM_{2.5}$ total. The relative uniformity of ozone and $PM_{2.5}$ contributes to their success as observable indicators of air quality, because it allows point measurements to be representative of community-scale exposures.

Day-to-day variations in concentration are driven principally by changes in atmospheric transport and dispersion. There are seasonal and weekly cycles in emissions, and major transients of smoke and dust can arise from "exceptional events" to be discussed later, but emission rates are generally much less variable than ambient concentrations are. Concentrations at a given location are affected by wind direction and the ventilation factor, the wind direction determining which sources are upwind and the ventilation factor governing the dilution of all emissions. Ventilation functions as an overall scaling coefficient that is influenced by large-scale factors such as mixing depth and wind speeds aloft. Point measurements of a spatially uniform pollutant thus capture some of the relative variation in all species' community-average concentrations, even those with unmonitored hot spots.

Figure 3 illustrates, in cartoon form, the potential of a broadly distributed pollutant to serve as an indicator of community exposures to unrelated local emissions. Line City is a collection of pollutant sources and two neighborhoods arrayed along an east-west axis. The two neighborhoods are bracketed by sources of the broadly distributed indicator species ***I***. The neighborhoods themselves bracket the sole source of ***X***, the primary pollutant actually affecting health. Each source generates a plume of effluent to the east or west depending on wind direction. Line City winds blow from the east on half of the days and from the west on the others. Both neighborhoods receive ***I*** emissions every day, but this ***I*** is mixed with unhealthful ***X*** in only one neighborhood at a time. Wind speed and mixing depth combine each day, independently of wind direction, to yield either good or poor synoptic ventilation. Only one of the two neighborhoods has air quality monitors. Because the ***I*** monitor always sees the effects of ventilation, even when the ***X*** monitor has nothing to measure, the ***I*** measurements give a better indication of community exposure to ***X*** than do the available measurements of ***X*** itself.

Availability of measurements and models

Ozone and $PM_{2.5}$ are among the six "criteria pollutants" routinely monitored for compliance with National Ambient Air Quality Standards (NAAQS) by Federal Reference Method (FRM) or Federal Equivalent Method (FEM). States, tribes, and local agencies establish and operate compliance networks following specific EPA guidelines for siting, instrumentation, and quality assurance. The resulting data are submitted to EPA's Air Quality System (AQS) database by the end of the quarter following the quarter of their collection. AQS is an attractive source of uniform, timely, and quality-assured air monitoring data.

Figure 4 compares the volumes of FRM/FEM data available for ozone and $PM_{2.5}$. FRM/FEM measurements are made daily at far more locations for ozone than for $PM_{2.5}$. Ozone was measured at this frequency at over 550 sites throughout 2006 and at over 1100 sites during peak ozone months, while daily $PM_{2.5}$ measurements were made at under 110 sites. Most FRM/FEM measurements for $PM_{2.5}$ are made once every three or six days.

The different frequencies of the FRM/FEM data for ozone and $PM_{2.5}$ reflect the networks' design for compliance monitoring rather than public health tracking. The health-based ozone NAAQS has always targeted extreme values, specifying an 8h (formerly 1h) concentration not to be exceeded more than a handful of days each year. Verifying compliance with a standard of this form requires continuous monitoring, at least during the season of high concentrations. The new $PM_{2.5}$ NAAQS introduced in 1997 included a limit on the annual mean as well as one on extreme 24h concentrations. The annual standard was generally controlling, in the sense that it was hard to violate the 24h standard without also exceeding the annual mean. Compliance monitoring for $PM_{2.5}$ therefore focused on the annual mean, which usually could be estimated from measurements on a representative sample of days. EPA significantly tightened the 24h standard in December 2006, and supported this change by moving to daily sampling at about 50 monitoring sites previously sampling one day in three (USEPA, 2006).

Non-FRM/FEM data for $PM_{2.5}$ are available on the every-third-day schedule of most FRM/FEM monitors from two networks that monitor particle speciation (VIEWS, 2007). IMPROVE (Interagency Monitoring of PROtected Visual Environments) operated about 160 sites in 2006, at predominantly rural or remote locations. CSN/STN (Chemical Speciation Network / Speciation Trends Network) operated about 60 population-oriented sites every third day and about 125 more every sixth day. These networks weigh 24h samples on Teflon filters as the FRM does, but use samplers with inlets and flow rates different from FRM specifications.

Daily $PM_{2.5}$ measurements are made at many more locations by continuous monitors, in support of EPA's AIRNow public-reporting program. About 580 sites throughout the U.S. currently supply real-time hourly data (Chan, 2007) that are reduced to broad ranges for display on a national map (Figure 5). The data are qualified as "not fully validated … [and] only approved for the expressed purpose of reporting and forecasting the Air Quality." They are password-protected from public access, but are available to stakeholder agencies (Chan et al., 2007). Various measurement methods are used, including beta absorption, nephelometry, and the most commonly employed, the Tapered Element Oscillating Microbalance (TEOM).

EPA excludes continuous $PM_{2.5}$ monitors from consideration as FEMs, but contemplates their inclusion as Approved Regional Methods (ARMs) in its overall monitoring strategy. EPA distinguishes ARM data from FRM/FEM data because particle measurements are sensitive to methodological details. Some ambient particles are in equilibrium with surrounding gases, an equilibrium that can shift after they are sampled onto an FRM/FEM filter through which air continues to be drawn. Because the $PM_{2.5}$ NAAQS is set in terms of the FRM, a method that avoided such sampling artifacts (or exhibited different ones) would not be suited to monitoring NAAQS compliance. Additionally, the continuous methods are not directly gravimetric and so require calibration factors that can vary with particle composition and ambient humidity. It is clearly undesirable to have site-specific calibrations influence compliance determinations that span diverse climates and regulatory jurisdictions.

Data quality objectives for EPHT differ from those for compliance monitoring, in ways that are more welcoming of AIRNow data. Compliance determinations address whether or not measured concentrations exceed a specified limit; avoiding errors requires measurements that are especially accurate at concentrations near that limit. Epidemiological analyses examine differences rather than absolute concentrations, and require only the correlation of a measurement with the variable of interest. It is correlation with the FRM that will qualify a method as an ARM: Mintz and Schmidt (2007) report an overall correlation of $r^2 = 0.77$ between 24h AQS and AIRNow $PM_{2.5}$ concentrations in over 110,000 paired observations during 2004-2006.

Whatever the density of a monitoring network and whatever the quality of its measurements, reported concentrations represent only a sample from the continuous atmosphere to which people are actually exposed. The relationship of inhaled air to monitored air is embedded in any observed statistical association between air quality and community health. City-scale studies have commonly modeled this relationship by treating individual exposures as Berksonian departures from a city-wide air quality that is estimated by averaging all local measurements in each monitoring period. Such simple models are consistent with the interpretation, sketched earlier, of ozone and $PM_{2.5}$ as generic indicators for broader chemical mixes. Without more detailed knowledge of individual activity patterns, it is unclear how much additional explanatory power could be gained from greater spatial resolution of concentration fields.

On the geographic scales EPHT is to cover, a model accommodating spatial gradients will be needed to relate measured concentrations to individual exposures. This model should reflect known emissions gradients and wind patterns. EPA's current operational-level understanding of these factors is incorporated in its Community Multi-scale Air Quality (CMAQ) grid model, which has been used since 2004 to produce real-time national forecasts of hourly ozone concentrations (NWS, 2007). CMAQ's $PM_{2.5}$ routines are much younger than its ozone routines, which trace their ancestry back through generations of critical scrutiny (e.g. NRC, 1991). A recent report (USEPA, 2005) found performance in the western U.S. to be significantly poorer for all $PM_{2.5}$ species than in the eastern U.S., which had been the early focus of evaluations. Users can expect CMAQ's $PM_{2.5}$ performance to evolve and improve as it undergoes more cycles of review and development.

CMAQ's primary function has been to support the evaluation of alternative strategies for managing emissions to attain ambient standards. It is accordingly source-oriented, taking emissions and winds as given and predicting the ambient concentrations that result under various regulatory scenarios. One limitation of any source-oriented $PM_{2.5}$ model is that elevated concentrations can result from sporadic and hard-to-characterize fugitive emissions. Unlike CO and SO_2, which emerge predictably from tailpipes and stacks through which their fluxes can be measured and documented, episodes of dust and smoke typically reflect agricultural and construction activities, wildfires, and other sporadic and diffuse sources. Even concentrations measured near such sources are not reliably convertible to the mass fluxes needed as model inputs. Ammonium nitrate, a sometimes-important secondary fraction, presents a similar problem; although tailpipe and stack emissions of NO_x are well accounted for, fugitive emissions of ammonia are not. Evaluations of CMAQ repeatedly show its sulfate prediction to exhibit the best agreement with measured 24h concentrations (Mebust et al., 2003; USEPA, 2005). It is no coincidence that SO_2, the precursor to sulfate $PM_{2.5}$, has perhaps the best-characterized emissions of any air pollutant.

CMAQ and the monitoring networks exhibit somewhat complementary strengths and weaknesses, suggesting that a fusion of the two might yield superior air data for EPHT. Point measurements represent “true” concentrations, as defined by regulations and the epidemiological findings that motivate them. However they have no necessary relationship to one another; in sparsely monitored areas they leave uncertain the boundaries between clean and dirty air. In contrast CMAQ yields a logically coherent grid of concentrations that reflects our understanding of emissions and atmospheric processes. These concentrations can be unrepresentative of reality, however, when they are derived from inaccurate descriptions of emissions and the atmosphere.

Model outputs could in principle be reconciled with measurements by adjusting uncertain model inputs. Prior probability distributions would be assigned to the intensity and geographical distribution of emissions, to wind fields, and to empirical parameterizations of atmospheric transformations, and then revised in light of observed concentrations. The iterations required for a fully Bayesian solution would be difficult to implement with the massive CMAQ code, although steps in this direction have been taken with simpler models. A less demanding approach to assimilating observations with CMAQ is the hierarchical Bayesian (HB) approach described by McMillan et al. (2007). Watkins et al. (2005) reported encouraging results from epidemiological explorations with HB-fused air data.

McMillan et al. used HB modeling to reconcile $PM_{2.5}$ concentrations from CMAQ and compliance monitoring in the eastern U.S. during 2001. In 2001 there were no data-quality objectives for continuous PM2.5 monitors (USEPA, 2002), and no collation and mapping of continuous data by AIRNow. In this setting the authors relied on FRM/FEM data for their observational inputs, reserving non-FEM measurements (from the IMPROVE and CSN/STN speciation networks) for cross-validation of the results. In 2004 and later years, the continuous $PM_{2.5}$ data reviewed by Mintz and Schmidt (2007) provide much fuller observational coverage of the space-time grid than the predominantly 1-in-3-day FRM/FEM data offer, and any inequivalence between them can be accounted for within the Bayesian framework. Incorporating the continuous data seems a natural next step for EPHT to explore, particularly given EPA’s announced intention to facilitate their substitution for filter-based FRM measurements in the future (USEPA, 2006).

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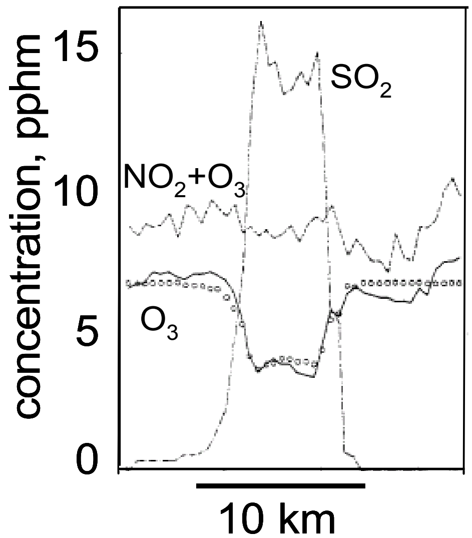
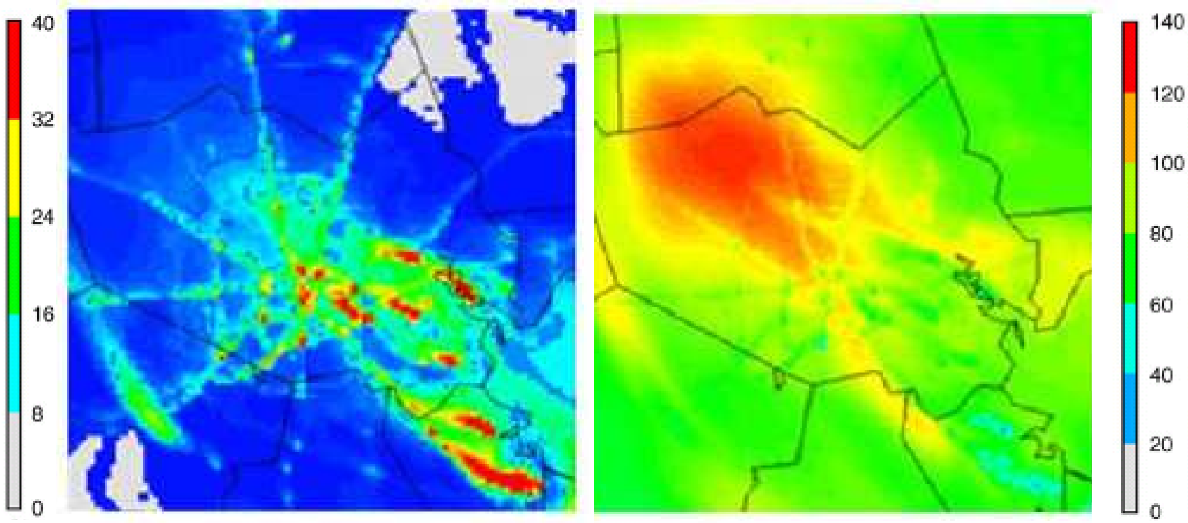
<u>Figure 1.</u> Right: Observed ozone deficit in a NO_x-rich power plant plume, from a traverse by instrumented aircraft (adapted from White, 1977). Circles show ozone profile from a simple photostationary model.

Below: Simulated NO_x (left) and O_3 (right) concentration fields in Houston, from a CMAQ model run at 1 km grid resolution (adapted from Ching et al., 2006). Arterial roads show NO_x excesses and O_3 deficits, as do source regions to the southeast.





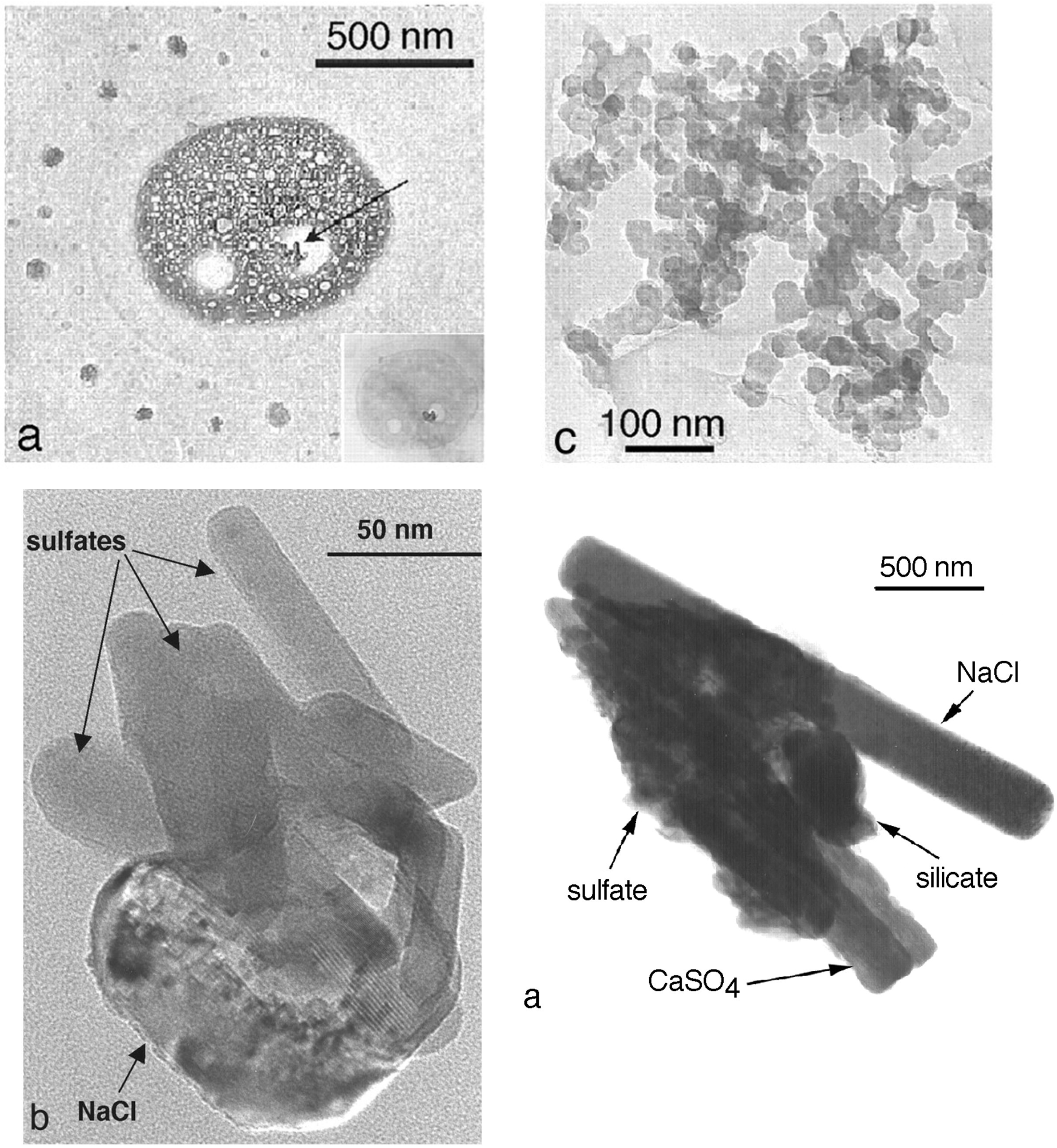


Figure 2. Electron micrographs of example atmospheric particles (NRC, 2004; adapted from Buseck and Posfai, 1999).
(a) Internal mixture of sulfate and soot; arrow points to a soot aggregate. The surrounding halo is ammonium sulfate crystals formed as the sulfate dehydrated in the microscope's vacuum.
(b) Sea salt.
(c) Branching soot aggregate typical of combustion processes.
(d) Internal mixture of terrestrial silicate with sea salt and anhydrite (calcium sulfate) likely formed by reaction of sulfur dioxide with carbonate particles.

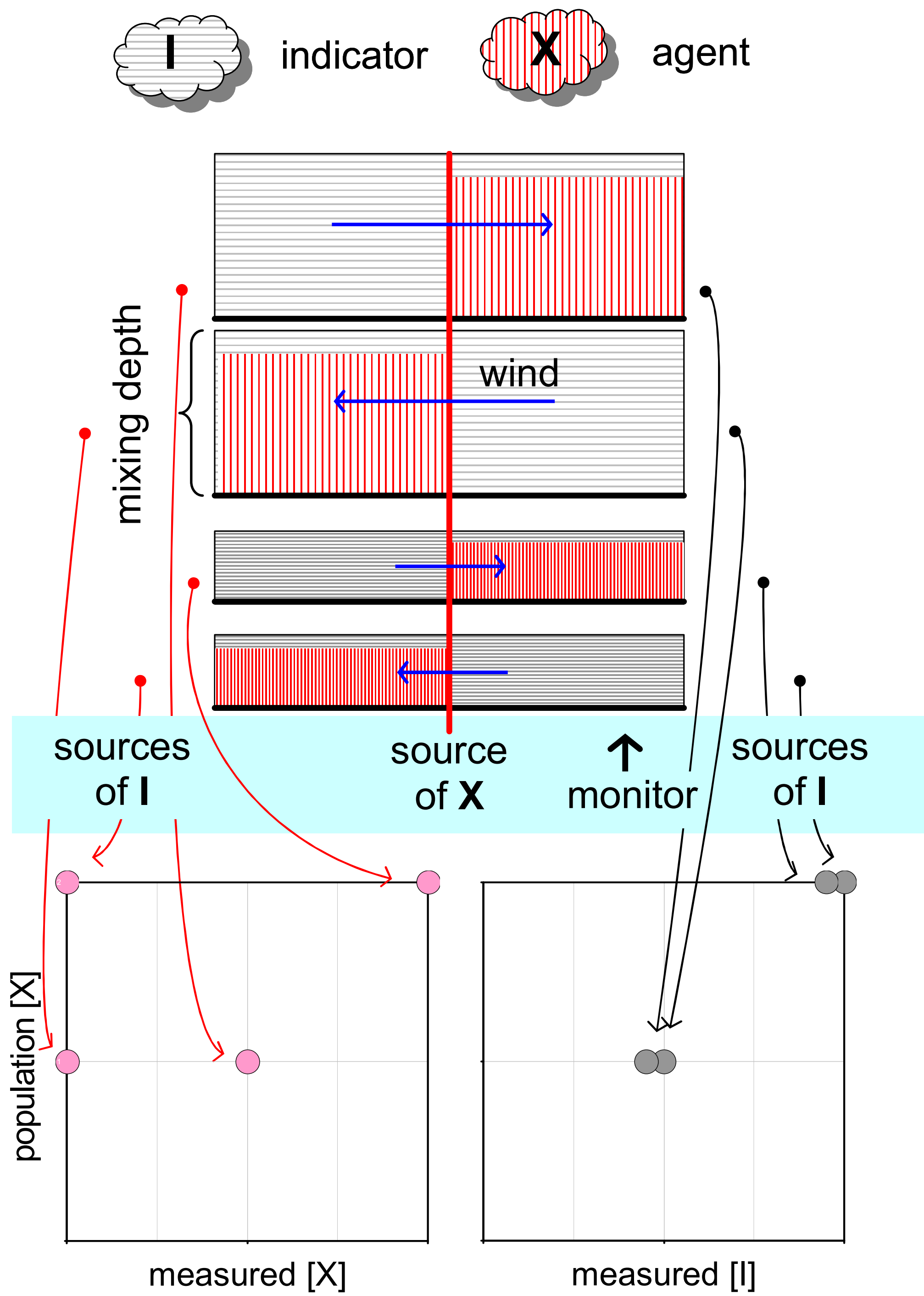


Figure 3. Pollution climate of Line City. Blue bar maps the linear arrangement of emissions sources and monitor. Rectangles above the bar show x-z distributions of atmospheric concentrations under four different meteorological regimes. Graphs below the bar plot city-average concentrations of the harmful agent **X** against monitored concentrations of **X** and the generic air quality indicator **I**.

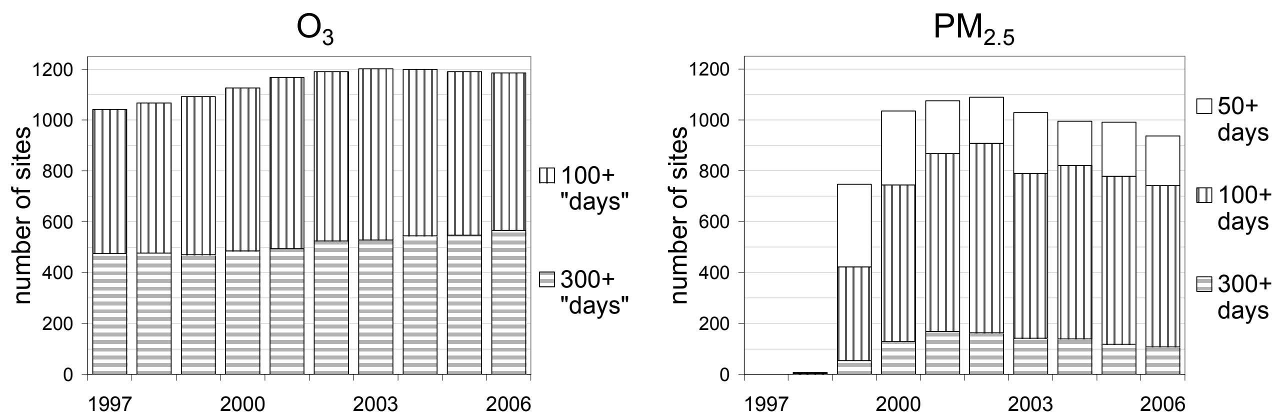


Figure 4. Trends in monitoring by the Federal Reference Method (FRM) or a Federal Equivalent Method (FEM). FRM and FEM monitors for ozone report continuously, year-round in some locations and during selected warm months at others. Measured "days" for ozone are plotted as reported hours/24. FRM and FEM monitors for $PM_{2.5}$ collect 24h samples year-round, daily or every third or sixth day. At sites with multiple monitors, only the one reporting the most observations was counted. Data were downloaded December 2007 from AirData, http://www.epa.gov/aqspubl1/annual_summary.html.

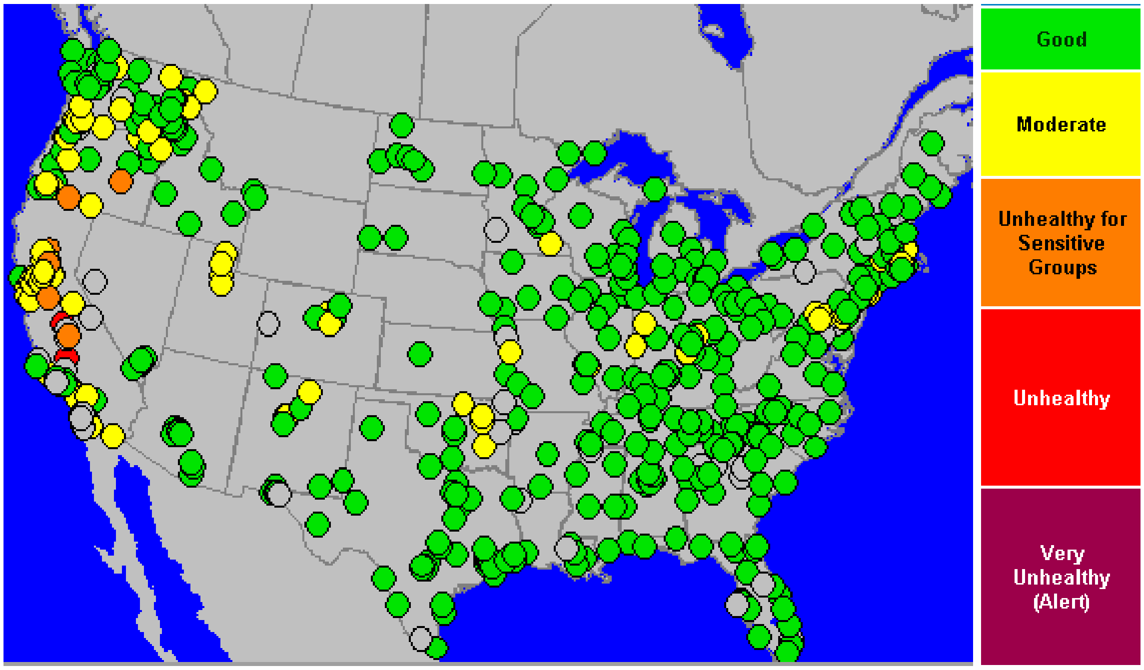


Figure 5. AIRNow map of 24h PM2.5 air quality indices on 12/14/07, captured 12/15/07 from http://airnow.gov/index.cfm?action=airnow.displaymaps&Pollutant=PM2.5&StateID=60&domain=super. Data are from continuous monitors not qualifying as FEM; nominal concentration ranges are $0 \leq$ green ≤ 15 ug/m^3, $15 <$ yellow ≤ 40 ug/m^3, $40 <$ orange ≤ 65 ug/m^3, $65 <$ red ≤ 150 ug/m^3, and 150 ug/m$^3 <$ purple.

ANNEX B4.

Bachmann J. Air pollution forecasts and results oriented tracking.

Air Pollution Forecasts and Results Oriented Tracking

John Bachmann, Vision Air Consulting

This paper provides a brief overview of recent EPA forecasts of air quality and emissions related to ozone and particle pollution. It is intended to supplement conference papers on air quality and benefits estimates by highlighting the potential utility of national, regional, and local forecasts in developing and implementing health and environmental quality tracking programs. As Hubbell and Fann (2007) note, such forecasts are of particular importance in evaluating the feasibility and design of programs intended to assess the benefits of air related control or mitigation programs. Tracking programs may focus on overall air quality improvements or on reductions from particular source categories of interest.

The Past as Prelude

Over the past three decades of the Clean Air Act, EPA state, local, and tribal agencies, other major stakeholders in the process, including the private sector, have worked to implement programs aimed at reducing emissions of those pollutants that contribute to poor air quality (Figure 1; Bachmann, 2007). The national-level trends in criteria pollutants and selected Hazardous Air Pollutants (HAP) shown in Figure 2 indicate the progress in air quality resulting from these programs. Of the six pollutants for which national ambient air quality standards (NAAQS) exist, only two—ozone and $PM_{2.5}$—remain persistent, widespread problems with concentrations above, or close to, the NAAQS. As is more evident in below, this situation is forecast to continue, particularly with the recent tightening of the PM standard and the proposed revisions to the ozone NAAQS.

National Emissions and Air Quality Forecasts

EPA recently promulgated a number of federal regulations to reduce multiple air pollutants. In 2005, EPA promulgated the “Clean Air Rules”, which included the Clean Air Interstate Rule (CAIR), the Clean Air Mercury Rule (CAMR), and the Clean Air Visibility Rule (CAVR). These rules target emissions of NO_x, SO_x, and mercury from power plants. In addition, EPA promulgated the Clean Air Nonroad Diesel Rule in 2004 aimed at reducing PM, NO_x, and SO_x from construction, agricultural, and industrial diesel-powered equipment. EPA has produced emissions and air quality forecasts for these as well as more recent programs. (EPA, 2005)

Figure 3 shows the projected changes in pollutant emissions between 2001 and 2020 including the reductions resulting from the Clean Air Rules implementation. As shown, with the exception of NH_3, all pollutants are expected to decline over this period with significant reductions between 30 and 50 percent for NO_x, SO_2, and VOCs. These declines demonstrate the effectiveness of CAA programs; however, the figure also shows the large remaining emissions across the eastern and western US in 2020.

Figure 4 shows recent and projected improvements in PM and ozone air quality resulting from the Clean Air Rules and other baseline emissions reductions programs. Recent significant improvements observed in these pollutants between 1999-2001 and 2003-2005 are primarily due to the acid rain program, the NO_x SIP Call, and mobile source programs implemented during this seven year period. The pollutant emission reductions expected by 2020 from these programs will result in still fewer projected nonattainment areas for ozone and $PM_{2.5}$. Ozone and $PM_{2.5}$ non-attainment is projected to continue in southern and central California areas. Ozone problems are forecast to persist in the Northeast corridor and Houston area, while $PM_{2.5}$ issues continue in midwestern cities such as Chicago, IL; Detroit, MI; and Cleveland, OH; as well as Birmingham, AL. These maps overstate non-attainment to the extent that do not include local or sub-regional programs that will be adopted to attain the standards. On the other hand, these figures do not include the 2006 $PM_{2.5}$ standard or possible strengthening of the ozone standards. Figure 5 projects baseline non-attainment in 2020 for a range of proposed ozone NAAQS alternatives.

Some Implications for Tracking and Accountability

Recognizing their inherent limitations, these national level forecasts can provide some indication of the extent of potential emissions and air quality improvements in particular areas expected over the next decade. This might provide some guidance to those seeking to track areas with the most significant reductions. In particular, those areas forecast to have continued non-attainment for ozone and PM in 2020 are those with a responsibility to develop additional control programs that attain the relevant standards. More area specific forecasts will be produced by areas as they develop their control strategies and implementation plans.

These forecasts can be broken according to specific source categories and particular areas. An examination of the historical trends and the time course of the emissions reductions indicate we are currently in a period with the highest rate of anticipated emissions reductions. Figure 6 shows forecasted national changes in mobile source emissions from on- and off road vehicles for direct PM and NO_x. The later year projections are more uncertain, but it appears tracking programs over the next several years have a better chance for detecting trends.

Trends, timing, and relative importance of local sources will, of course vary with location. In addition, uncertainties in these emissions inventories may be significant, especially for mobile source PM emissions. The relative change forecast for mobile emissions is large for both particles and gases. Given increasing evidence of increased health risk with proximity to traffic, it would be of some interest to examine the feasibility of detecting trends in areas with greater than average reductions forecast for direct PM and pollutant gases. The national forecasts suggest that such tracking programs should begin soon, if they are not already underway, as we are already moving into a period of maximum change for both on and off-road sources. The absolute PM reductions forecast appear small but recent comparisons of emissions data with air quality data suggest the contribution of direct mobile source PM is substantially larger than implied by the emissions data (EPA, 2006). While overall mass will decline, the trends for near-roadway ultrafine particles are less clear. Reductions in fine particle mass can increase ultrafine particles, but some technologies reduce both and the reduction in roadway SO_2 and NO_x will also affect secondary ultrafine particle production.

Because stationary sources of fine particles are also declining at the same time and the overall change from year to year is modest, those interested in near roadway trends might want to consider targeting tracking programs to areas with the best ‘signal to noise’ for such sources. A number of areas are implementing or planning interventions that reduce existing diesel emissions faster than the national new source regulations. They involve school bus and fleet retrofits and programs to address existing marine emissions. Examples include the West Coast Diesel Emissions Reductions Collaborative, the Midwest Clean Diesel Initiative, and the Rocky Mountain Clean Diesel Collaborative (EPA, 2008). Areas affected by these programs should have faster than average improvements in diesel PM and related gas emissions, The patterns of emissions and reductions will vary in port cities, such as Seattle, as compared to areas with programs that only school buses and fleets. It may be easier to detect the effect of highway emissions in such areas, and a comparison of areas with and without interventions, as well as comparing eastern (with additional regional PM reductions) to western areas. From a within-city point of few, there may be advantages for a cross-sectional study in a port city with major near road and near port gradients in exposures to marine and terrestrial emissions.

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ANNEX B

Acknowledgements

I appreciate the access to relevant spreadsheets and figures provided by EPA's Norm Possiel (Office of Air Quality Planning and Standards) and Joseph Somers, (Office of Transportation and Air Quality).

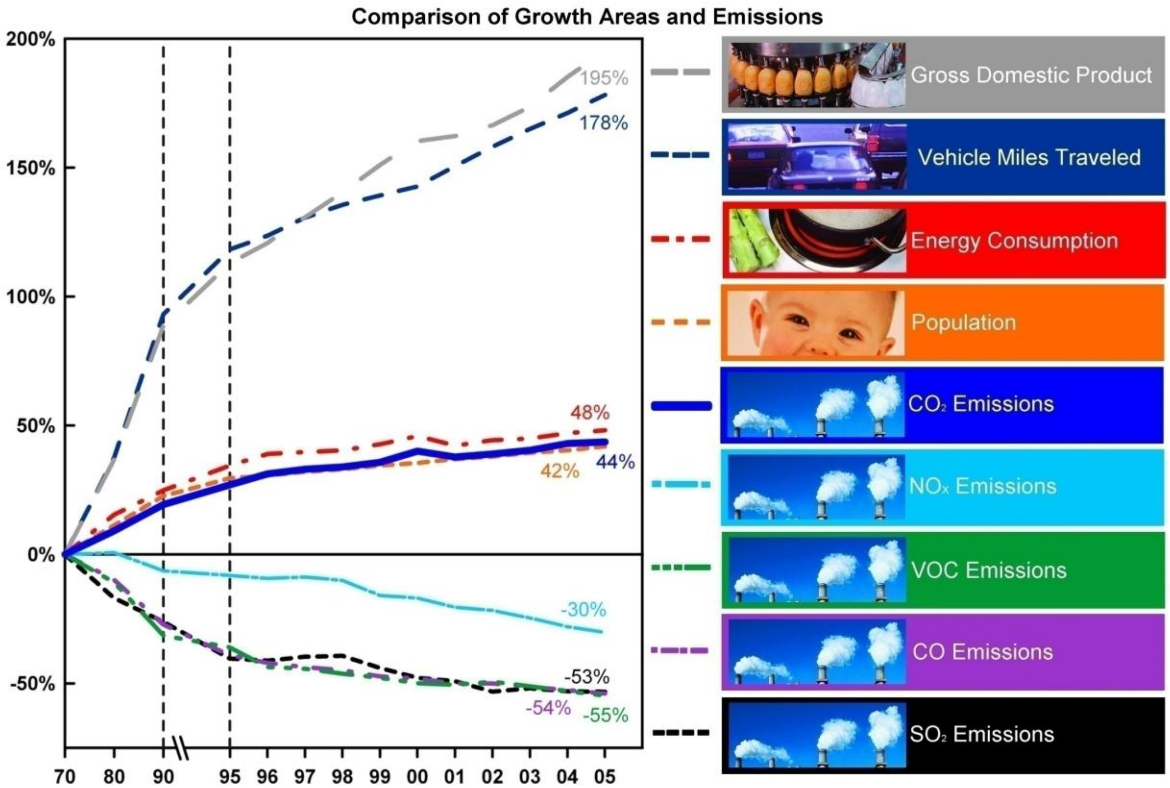

Figure 1. National Emissions Trends. Clean Air Act programs effected substantial emissions of targeted pollutants as compared to CO2, which was not.

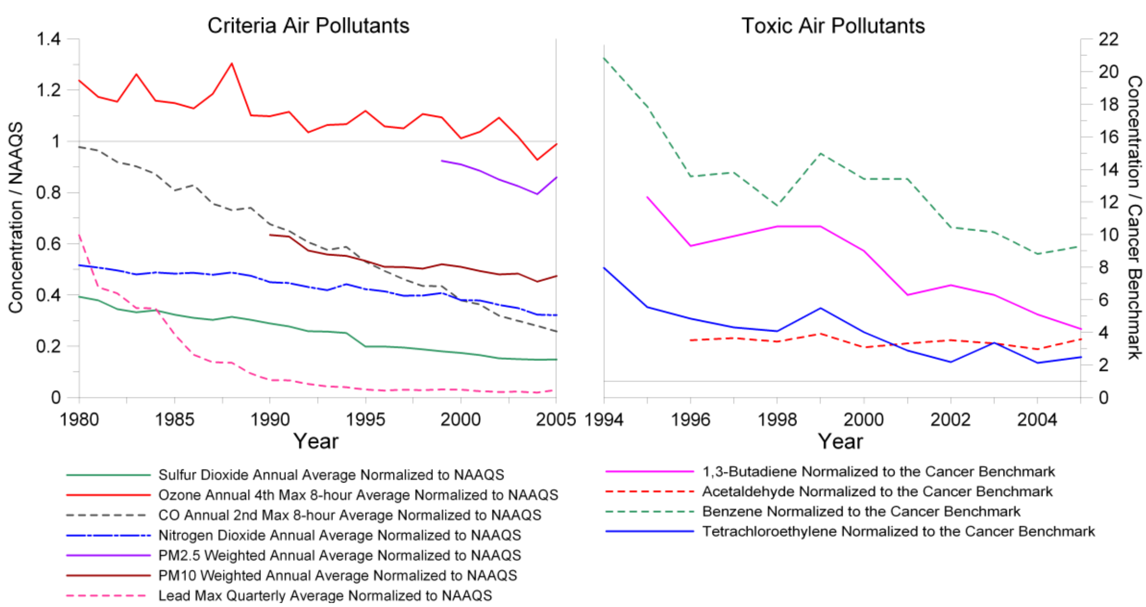

Figure 2. National-level trends in criteria and selected HAPs relative to the NAAQS and cancer benchmarks Criteria pollutant programs contributed to reduction of specific toxic materials, including some automotive VOCs.

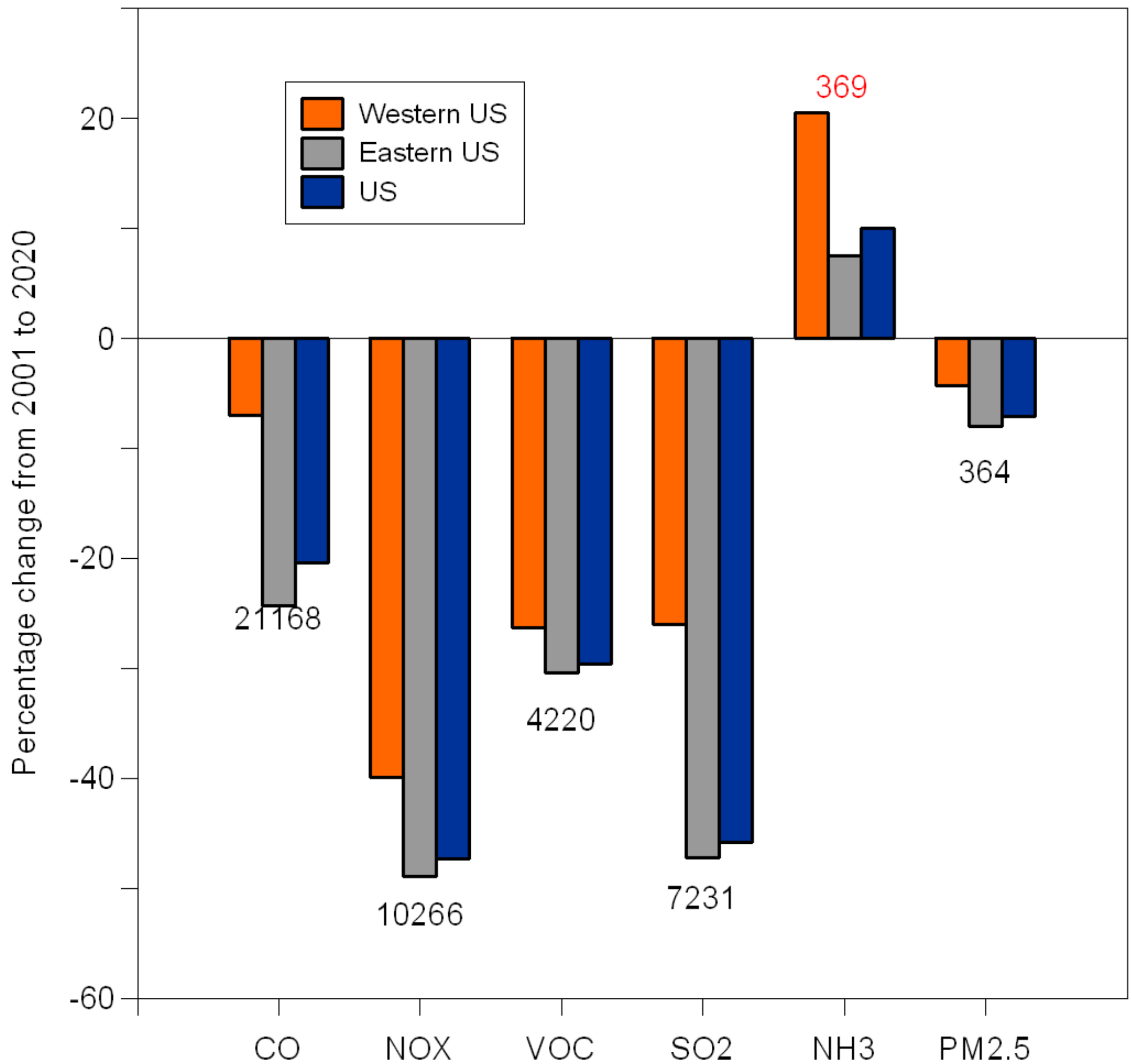

Figure 3. Projected changes in pollutant emissions between 2001 and 2020 resulting from the Clean Air Rules and other baseline programs (see text). Numbers near each set of bars is the reduction or increase) in thousands of tons. (EPA, 2005).

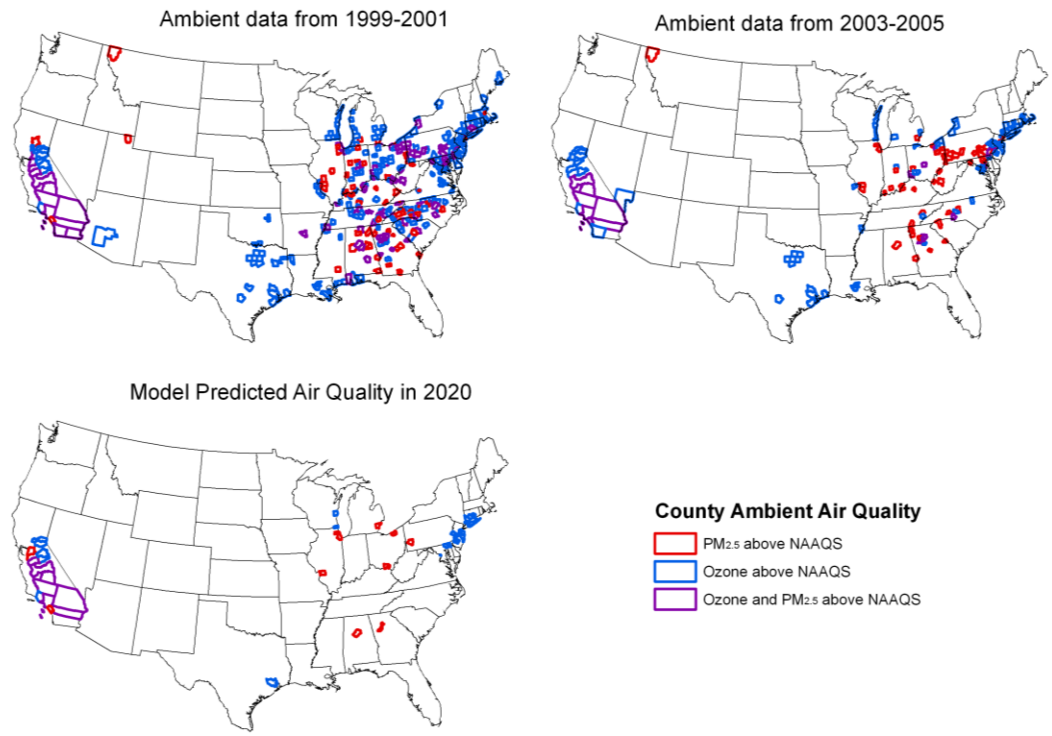

Figure 4. Recent and projected ozone and $PM_{2.5}$ air quality, 1999-2020 (after EPA, 2005).

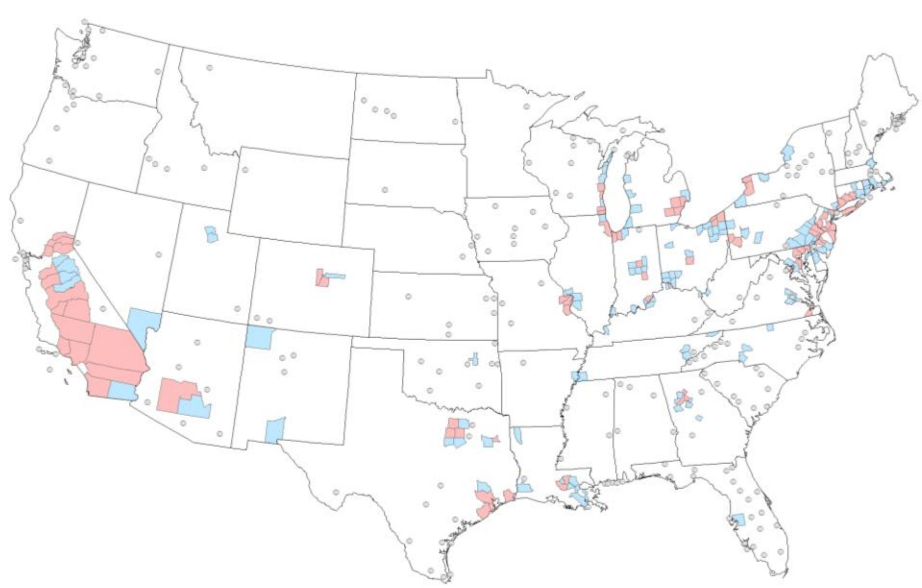

Figure 5. Counties with monitors projected to violate proposed 8-hr ozone standards of 0.070 and 0.075 ppm in 2020. Based on preliminary modeling (EPA, 2007b).

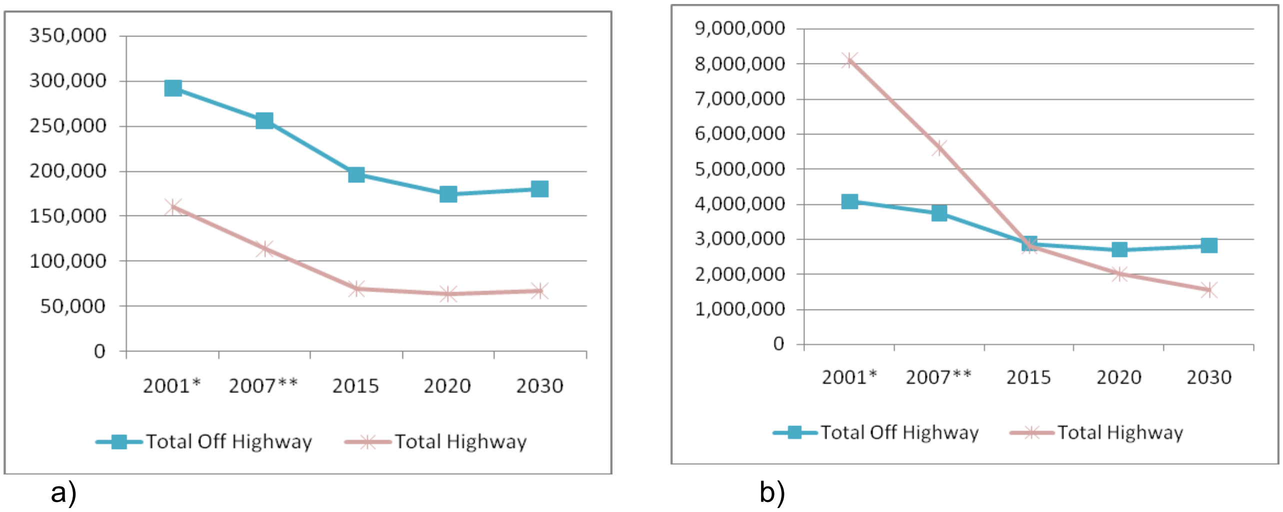

Figure 6. Forecast mobile emissions for a) direct $PM_{2.5}$ and b) NOx in tons. The rate of observed/projected reductions is larger between 2001 and 2015 than in later years. Similar patterns are seen for mobile VOC and stationary NOx/SO_2. (Somers, 2007).

ANNEX B5.

Talbot TO, Haley VB, Dimmick WF, Paulu C, Talbott EO, Rager E. Developing consistent data and methods to measure the public health impacts of ambient air quality for Environmental Public Health Tracking: Progress to date and future directions.

ANNEX B

Title: **Developing consistent data and methods to measure the public health impacts of ambient air quality for Environmental Public Health Tracking: Progress to date and future directions.**

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Centers for Disease Control and Prevention,
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Introduction

The state and national Environmental Public Health Tracking (EPHT) Programs are building a network of integrated health and environmental data to provide nationally consistent data and information related to environmental health. These will be used to perform a variety of environmental health surveillance functions such as monitoring trends in environmental hazards and disease, exploring relationships between environmental hazards and disease, identifying populations at risk, and guiding intervention and prevention strategies (www.cdc.gov/nceh/tracking).

Participants from academic institutions, the US Centers for Disease Control and Prevention (CDC), state health departments, data steward organizations, and environmental agencies across the country are working together in teams to define the nationally consistent data and indicators that will be part of the Network. In September 2006 the EPHT Air Team was formed to "develop recommendations for ambient ozone and $PM_{2.5}$ data sets; for tools (including analysis and visualization); indicators and combined air quality and health measures and metadata to be included in the National Environmental Public Health Tracking Network." The EPHT Air Team is currently focusing on ambient levels of ozone and $PM_{2.5}$ because these data are routinely collected across the country and there are established associations of these pollutants to adverse health outcomes such as myocardial infarction and asthma. The Air team is collaborating with another EPHT Team that focuses on the use of cardiovascular and respiratory disease hospitalization data for environmental health surveillance. Together, these EPHT teams are exploring how to produce and disseminate current and easy to use air-health impact indicators and other findings to the public, environmental health professionals, and policy-makers.

Health and environmental agencies have a long history of tracking trends in health and environmental factors separately. For example, EPA and many state environmental agencies monitor ambient air to ensure that it meets regulations and they disseminate reports describing geographic and temporal trends in air pollution. The CDC and state health agencies track trends in cardiovascular and respiratory diseases through survey data, hospital administrative data and mortality registries.

The EPHT Teams seek to add value to the current surveillance systems by facilitating the analysis of linked health and air quality data in order better characterize the ambient air-health relationships and measure public health impacts. In principle, the surveillance of public health impacts related to ambient air quality can indicate the effectiveness of large-scale environmental regulations, and of regional or local intervention efforts. EPHT analysis of ambient air-health relationships can potentially help identify susceptible sub-populations, the relative potency of individual air constituents, and changes in sensitivity and potency over time. Surveillance of health outcomes related to ambient air quality can also generate hypotheses requiring further research. It is important to note that EPHT's activities are not meant to become or usurp an ambient air epidemiology research program; rather, the goal is to integrate some analytic methods into routine surveillance. The key issue for EPHT is how to "track associations" between ambient air and health outcomes in a consistent, reliable, and sustainable manner that supports public health practice (Paulu).

Routinely estimating the regional and local associations and public health impacts of air pollution on health is an important component of EPHT. Focused studies of the relationship between air quality and health outcomes by EPHT states may lead to program activities to address the adverse outcomes of exposure to air pollutants. A number of studies have shown that the association between ambient concentrations of ozone and $PM_{2.5}$ and morbidity and mortality varies between geographic areas. Temporal and geographic differences may be due to differences in the vulnerability of the populations, health care practices, and the pollutant mix, as well as random error or bias in the data and statistical models used to estimate concentration-response relationships. Using local data to provide local and updated impact estimates could be used to more accurately communicate risk and guide research and public health practice.

Another benefit of generating public health impact estimates is that the information can more clearly communicate the effects of air pollution to policymakers than separate air or health indicators. While it may be useful to report that the average annual $PM_{2.5}$ level in a city is 10 ug/m^3, it may be more informative to report the magnitude of health impacts such as the number deaths or years of life lost attributable to these levels. For example the Air Pollution and Health European Information System (APHEIS) has been established to systematically assess and communicate this information (Boldo et al 2006). In Phase 3 of the project APHEIS used the results of cohort studies to quantify the public health impacts of long term exposures to $PM_{2.5}$ in 23 European cities using. EPA periodically conducts national level health impact assessments to estimate the costs and benefits of proposed regulations (EPA 1999, 2004). Several groups have performed similar analyses at the substate level to analyze more local air quality issues (see review in workshop white paper by Hubbell). However, within the U.S., the health burden of air pollution is not regularly reported for local areas as part of public health practice.

This paper will focus on the EPHT program's progress to date on developing consistent data and methods to measure the public health impacts of ambient air quality. We describe the types of air quality and health outcome data that will initially be available and how they might be used to estimate associations and public health impacts of ambient levels of ozone and $PM_{2.5}$. We list some of the major activities to create nationally consistent data, estimates of public health impacts and associations and the obstacles which will need to be overcome in order to produce measures of air-health impacts which meet the needs of a variety of stakeholders.

EPHT Data

The EPHT network will provide access to a wide range of standardized health and environmental data and indicators from the participating state and national networks (CDC 2006). These will be made available to users at varying levels of detail and with levels of security commensurate with the sensitivity of the data. This section will describe the air and hospitalization data that will be available on the EPHT network.

Air Data

The AQS database (http://www.epa.gov/ttn/airs/airsaqs/index.htm) contains ambient air pollution data collected by EPA, state, local, and tribal air pollution control agencies to assess air quality, assist in attainment vs. non-attainment designations, prepare reports for Congress as mandated by the Clean Air Act, and perform other air quality management functions. AQS also contains meteorological data, descriptive information about each monitoring station, and data quality assurance and quality control information. There are roughly 1,000 monitors across the US that measure ambient ozone and 1,000 that measure PM2.5.

The AQS data are generally considered to provide the most accurate estimates of air quality at a given time and place, however the times and locations with data are limited. The locations of monitors do not coincide exactly with the times and locations of health events. The AQS have been used in the vast majority of U.S. studies linking health and air quality data. Many different approaches have been used to assign exposure levels to the health data. These methods range in complexity from assigning the nearest monitors or the average of monitors within a county, to interpolating concentrations across space using interpolation techniques (variogram analysis).

The EPA Community Multiscale Air Quality (CMAQ) modeling system is one model that incorporates the important physical and chemical functions associated with the dispersion and transformations of air pollution. CMAQ approaches air quality as a whole by including state-of-the-science capabilities for modeling multiple air quality problems, including tropospheric ozone, fine particles, air toxics, acid deposition, and visibility degradation. CMAQ relies on emission estimates from various sources, including the U.S. EPA Office of Air Quality Planning and Standards' current emission inventories, measured emission rates from major utility stacks, and model estimates of natural emissions from biogenic and agricultural sources. CMAQ also relies on meteorological predictions that include assimilation of meteorological observations as constraints. Emissions and meteorology data are fed into CMAQ and run through various algorithms that simulate the physical and chemical processes in the atmosphere to provide estimated concentrations of the pollutants. The grid resolutions for CMAQ are typically 36km x 36km per grid for the "parent" domain, and nested within that domain are 12km x 12km grid resolution domains. The parent domain typically covers the continental United States, and the nested 12km x12km domain covers the Eastern or Western United States. Currently, 12km x 12km resolution is recommended for most applications as the highest resolution. With the temporal flexibility of the model, simulations can be performed to evaluate longer term (annual to multi-year) pollutant climatologies as well as short term (weeks to months) transport from localized sources. Improvements will be made to the CMAQ modeling system as emission inventories and chemistry models are further developed by the scientific community. For more information on CMAQ, go to www.epa.gov/asmdnerl/CMAQ or www.cmascenter.org.

The EPA statistically based ambient air estimates result from the combination of the AQS monitoring data with CMAQ modeled data using a hierarchical-Bayesian space-time statistical model (McMillan et al. in preparation, Banerjee et al. 2004, Holland et al. 2003). This approach attempts to combine the best characteristics of each source of spatial information for prediction over time when both sources of data are available. The model assumes that each source provides information about the underlying true pollutant surface. Air monitors are assumed to measure the true pollutant surface with some measurement error, but no bias. In contrast, numerical model output is assumed to approximate the variability of the true surface while exhibiting both measurement error and bias (additive and multiplicative) across space and time. Also, the model allows for the inclusion of covariates, such as daytime population density, to account for possible pollution-population relationships.

This Bayesian hierarchical space-time model gives more weight to accurate monitoring data in areas where monitoring data exists and relies on bias-adjusted model output in non-monitored areas. The model assumes that both monitoring data and CMAQ data provide good information about the same underlying pollutant surface, but with different measurement error structures. This approach offers the ability to predict important pollution gradients and uncertainties that might otherwise be unknown using interpolation results based solely on air monitoring data. These surrogate measures of air quality can be compared to adverse health outcomes.

Table 1 compares the features of the two types of air quality data being being proposed for use in EPHT. (1) ambient air quality monitoring data from the Air Quality System (AQS) and (2) statistically based ambient air estimates that result from monitored and modeled air quality data. The datasets will provide alternate characterizations of daily 8-hour maximum ozone concentrations and daily average PM2.5 concentrations. Each method has its own strengths and weaknesses, and either could be used to create air quality or linked air-health indicators or analyses.

Health Data

Participating EPHT state health departments will be collecting standardized data on hospital inpatient admissions for asthma and acute myocardial infarction. These data will provide important new information for disease surveillance, because there is currently no national database that consistently collects universal hospital discharge data for every state. National surveys such as the Behavioral Risk Factor Surveillance System (http://www.cdc.gov/brfss) have been used in the past, but these data do not provide incidence or prevalence data at the local level. Forty-six states and the District of Columbia collect hospital discharge data according to individual state laws. The data elements are reasonably well standardized as they are often derived from the Uniform Hospital Discharge Data Set. They include day and time of admission, primary and secondary discharge disease diagnosis, the address, and the date of birth which can be used to calculate age.

The challenge with creating a nationally consistent hospital discharge dataset is that many of the fields of interest, including ZIP code and date of admission, are considered to be confidential. States vary in their policies that permit use of these data. Generally, access to these fields requires completion of a review process by the data stewards and/or an Institutional Review Board process on the basis of an individual study. Thus, the states and health care providers may continue to their control of individual level health records. Providing confidential data to the National EPHT network may not be feasible. The National Network however will provide access to aggregated data and public health indicators such as numbers and rates of inpatient hospital admissions summarized by year and county.

Hospitalization data stewards have recently begun to augment the databases of hospital inpatient stays with data on emergency room (ER) visits. In New York, there are approximately three and a half times as many emergency room visits for asthma as there are inpatient admissions, greatly improving case ascertainment. ER indicators may be added to national network when more data become available.

Future indicators either at the state or national level may require access to ZIP Code level health data. Counties are large, containing diverse neighborhoods with varying disease and risk factor rates, so smaller areas are needed to preserve the geographic variability of the information. For example ZIP code level maps, smoothed or aggregated to preserve confidentiality, could identify sub-county areas in need of additional public health programs. Furthermore, analyses of the short-term effects of pollution will require access to daily confidential health data.

Based on these issues, the hospitalization team could recommend that a partially de-identified subset of the data containing daily counts of admissions by ZIP code be made available on a secure state network for EPHT analyses. It is as yet unknown to what extent agreements can be negotiated that would allow access to these data by health department staff for routine surveillance, versus whether the data can only be made available for a more specific protocol after IRB approval.

Linked data

In order to measure the impacts of ambient air quality on cardiovascular and respiratory disease hospitalizations the data need to be linked both in time and by geography. The hospitalization records can either be geocoded to the street address, or the ZIP code centroid. This provides geographic coordinates for each hospitalization record. The air monitoring data or statistically derived air pollution data also contain geographic coordinates along with the dates for which the air pollution levels are estimated. This allows for the linking of the data by day and location (Haley et al).

This type of linked data set would be considered confidential by the data stewards since both day and geographic coordinates are provided for each case, so it might not be placed on a state or national EPHT network. Access to the underlying health data requires specific protocols be approved by the IRB and/or the data stewards, and that data be destroyed when the analyses are completed. For example, in one EPHT project, the New York, Wisconsin and Maine departments of health obtained approval to share hospitalization data among the states creating a combined linked dataset that each state could use to answer specific questions. Each state negotiated with their state specific IRB/Data owners for approval to share with the other states. Once the project was completed the dataset was destroyed. In the future, more flexible agreements are desired that will allow EPHT staff longer term access to confidential data. This will facilitate the use of newer, more advanced, and more useful surveillance methods by eliminating lengthy project-by-project IRB and data steward approval processes, and preserving cleaned geocoded data.

One option being discussed within the EPHT program is for each state to prelink the air and confidential health datasets, and then remove some of the confidential fields prior to making it accessible on the national network. For example, one could create an analytical dataset to measure the short term health effects of air pollution using case-crossover analysis; the dataset would contain the required case/control information linked with air pollution, weather, and ZIP code level socioeconomic data without giving the ZIP code or date of admission. However, this dataset could be deconstructed by a computer-savvy individual to reveal the actual date and ZIP code, by matching to the publicly available air pollution, weather, and SES data. It would be difficult to create such a dataset that would retain analytic capability without compromising the confidentiality of the data. A linked data set with less temporal and geographic resolution would not be as useful. For example, with such a data set it would be difficult to assess whether the associations of air pollution and health outcomes vary between neighborhoods with different socioeconomic status. The analyst would lose the ability to geographically identify areas with vulnerable populations or assess areas or time periods with large residuals since ZIP code and date would not be available. Another option is to develop a mechanism for people to access and analyze the confidential data without ever having to "see" it. Software programs could be developed that would allow users to run the analysis and return only the results which are non-confidential. This might put a burden on the data stewards who typically do not manage hospitalization databases in a geographic format that could be easily linked with other datasets.

The data stewards could develop an agreement with the state EPHT programs to help with this task. The software however would be difficult to design such that the data exploration and analysis methods could be flexible while preventing the inadvertent release of confidential data.

The health impacts of air pollution can also be reported at a cruder resolution by applying "off-the-shelf" concentration-response(C-R) functions to air quality data and summarized health data. For example, estimation of the long-term health effects of $PM_{2.5}$ cannot be calculated using raw surveillance data; these health impacts are based on C-R functions from cohort studies. Thus, health and air quality data by county and year could be used for producing county level impact air quality-mortality indicators.

Figure 1 summarizes the interaction among the EPHT air quality and health data, simple air and health indicators, linked air-health analyses and indicators, Census data, and external C-R functions. The EPHT analyses are shown to focus on identifying temporal, geographic, demographic differences in C-R functions, though they would be considered for use in producing impact indicators for the public and policy audience.

Progress to date (2002-2007)

In the first years of the EPHT project (2002-2005), CDC, EPA, and the health departments of New York, Wisconsin, and Maine collaborated in the Public Health Air Surveillance Evaluation (PHASE) Project. As part of this project, the three state health departments worked in parallel to estimate the short-term effects of $PM_{2.5}$ and ozone on hospitalizations within their respective states using one year of statistically combined air pollution developed by EPA. The PHASE team selected the EPA's statistically combined air quality data primarily to fill in the missing space and time components of the air monitoring data while maintaining the "ground truth" found in these data. They calculated statewide estimates of relative risk (e.g., percent increase in risk of hospitalization per 10 ug/m^3 increase in $PM_{2.5}$) and the corresponding absolute risk (i.e. number of hospitalizations triggered by the acute impacts of ozone pollution above background levels in 2001) using case-crossover analysis. In addition, since Maine Department of Health had access to 4 years of emergency room data they also measured the association between asthma emergency room visits and ambient air quality over a longer period of time (Paulu et al.)

The PHASE team selected case-crossover analysis due to the shorter learning curve and because the method can accommodate assigning exposure estimates to individual subjects in a straightforward way and single analysis. Case-crossover has been shown to be a comparable and alternative methodology to Poisson time-series regression analysis (Lu and Zeger 2006). In this design, cases serve as their own controls. A subject's exposure near the time of a health event (case-period) is compared with exposures at previous or subsequent points of time when that subject was a non-case (control-period). Case-crossover has been shown to be a comparable and alternative methodology to Poisson time-series regression analysis (Lu and Zeger 2006).

One of the strengths of the case cross over lies in the fact that control of variables like age, gender, ethnicity or area are not required as in a time series because cases are their own controls. This design can also be used to assess effect modifiers. With this study design we might explore if the C-R function varies over time, between sociodemographic groups or with proximity to specific sources of pollution. For example, Xu, Talbott et al. conducted a case-crossover analyses in an area near Pittsburgh where a steel coke plant had operated for many years. The study revealed reductions in cardiorespiratory disease hospitalizations associated with reductions of ambient levels of course particulates (PM_{10}) with the closing of the plant. In addition this study indicated a decrease in the C-R function as measured in the number of cardiorespiratory hospitalizations per unit change in ambient levels of course particulates (PM_{10}). This change in the C-R function could be the result of the changes in the composition of the particulate matter due to the closing of the plant.

The PHASE Team developed a technical background report summarizing the methodology (Haley et al 2007) and the Case-Crossover Analysis Tool (C-CAT) to facilitate the calculation (Abraham 2007), so that the analyses could be more easily carried out in the future with additional state partners and years of data. Though a tool and background report have been developed for this type of approach it still takes a trained public health professional with knowledge of biostatistics and epidemiology to conduct the analyses.

Discussions within the EPHT Air Team explored how EPHT states would use the results from linking air quality and health data. For example, how would states handle different, inconsistent or even protective, effect estimates? As a result of these discussions, the EPHT Air Team divided its linked air quality-health activities into two parts: creating linked air quality health impact indicators and performing linked air quality health analyses.

The linked air quality health impacts would be designed to inform the public, environmental health professionals, and policy-makers with current and easy to use information about the impact of air pollution on public health. They can be calculated by applying appropriate, peer-reviewed C-R functions to health and air quality data. The limitation of this type of method is that C-R functions developed in other geographic areas or during other time periods may not be directly transferable. C-R functions could vary due to many factors such as differences in the susceptibility of the population, access to health care, medical treatment, exposure, and pollutant mix. To address this limitation, linked air quality health impact analyses can be performed using EPHT linked air quality health analyses, resulting in C-R functions that may be more appropriate for the populations in question.

Linked air quality health analyses would involve analyzing, for state or sub-state areas, the association between air quality data and health tracking data, identifying statistical relationships. Such analyses could describe the degree to which individual-level risk factors such as age and co-morbid conditions, and community level risk factors such as poverty, modify the association between air pollution and health outcomes. The analyses can also track time trends in the relationship between air pollution and health(cite Paulu, Burnett). The resulting C-R functions, if properly quality assured, could serve as a basis for tracking air quality health relationships and information to use in targeting further preventative public health activities. In the future, the EPHT program could statistically combine analyses from multiple states to more robustly estimates of these relationship for special subgroups, following the methodology of other multi-city or multi-state projects such as NMAPPS (Dominici F, McDermott A, Zeger S, Samet JM. 2003) and APHEIS (LeTertre et al. 2005).

The development of indicators and analysis of association (C-R functions) for local-specific health impacts are challenged by other factors as well. First, the effect of ambient air pollution on health events is relatively small and imprecise. For example, the relative risk of cardiopulmonary mortality measured in the American Cancer Society Cohort (Krewski 2005), which is often used in estimating the long-term risk of pollution, was estimated to be 1.09, with a 95% confidence interval of 1.03 to 1.16 per 10 ug/m^3 $PM_{2.5}$; the range of uncertainty of the risk estimate was larger than the risk itself. Second, the health impacts of air pollution are entwined with the impacts of other risk factors; changes in the amount of exposure to one risk factor will modify the importance of other risks.

Despite these uncertainties, estimated local health C-R functions and indicators can provide information to assist policy-makers in the decision-making process. For example, estimates of the health burden attributable to air pollution and the burden attributable to smoking might be imprecise, but broadly interpreted, the data could help a state health department to allocate resources and select interventions. Through the process of continuous improvement and development of practical and uniform methods, health impact assessments will become more accurate. Local C-R function can lead to understanding differences in subpopulations, exposures, public health practices and air quality properties (e.g., chemical species). This will hopefully lead to improved air quality and public health programs

Future activities

The air and hospitalization EPHT teams are currently developing nationally consistent health and air quality data that can be routinely used to calculate measures of association and public health impacts of ozone and $PM_{2.5}$. The interagency agreement between CDC and EPA calls for the production of daily statistically-derived pollutant concentrations across continental US between 2001 and 2005 with the hope these estimates will be produced annually thereafter.

Though the air data will reside on a national network it is not yet clear where nationally consistent health and linked air-health data will reside due to confidentiality concerns. Will these data be held with the data stewards, the state EPHT or national EPHT networks? CDC will need to work closely with state health departments and data stewards to address this question. If the health and linked health-air data reside on a national network, agreements will need to be developed between CDC and the data stewards on how the data is used and released. The public health messages that are developed on a national network will also need to be consistent with the messages that state health and environmental agencies produce.

The Air Team is currently considering the development of measures for linked air quality and health data, both analysis and impact indicators. This information would be used within the EPHT program to direct public health action, inform policy decisions and communicate the state of air quality and public health to the public.

Communication of air quality health information is important for the EPHT network to highlight its environment-health approach. The linked information can be developed using applicable data, standardized procedures/models, and off-the-shelf C-R functions. It will be important for the EPHT team to understand how the public health messages disseminated by APHEIS and other groups have been received by the public and policy makers as the EPHT team defines the specific indicators and use desired for EPHT. Clearly defining the intent and audience for the indicators will be an important first step. For example, we could report the excess number of heath events or years of life lost due to air pollution levels above background concentrations, which assume no anthropogenic emission sources. In the context of evaluating policy changes, more specific scenarios, like a ten percent reduction in expected ozone levels based on changes in air emission policies, could be evaluated.

Additional work and training will be needed to develop and implement consistent methods that can be used to routinely estimate associations and impacts. Further development is necessary to apply statistical methods that "borrow" information from the combined set of state-specific C-R functions to come up with new state-specific estimates. Among a number of technical and scientific issues, the new methodology will need to consider individual and neighborhood level effect modification.

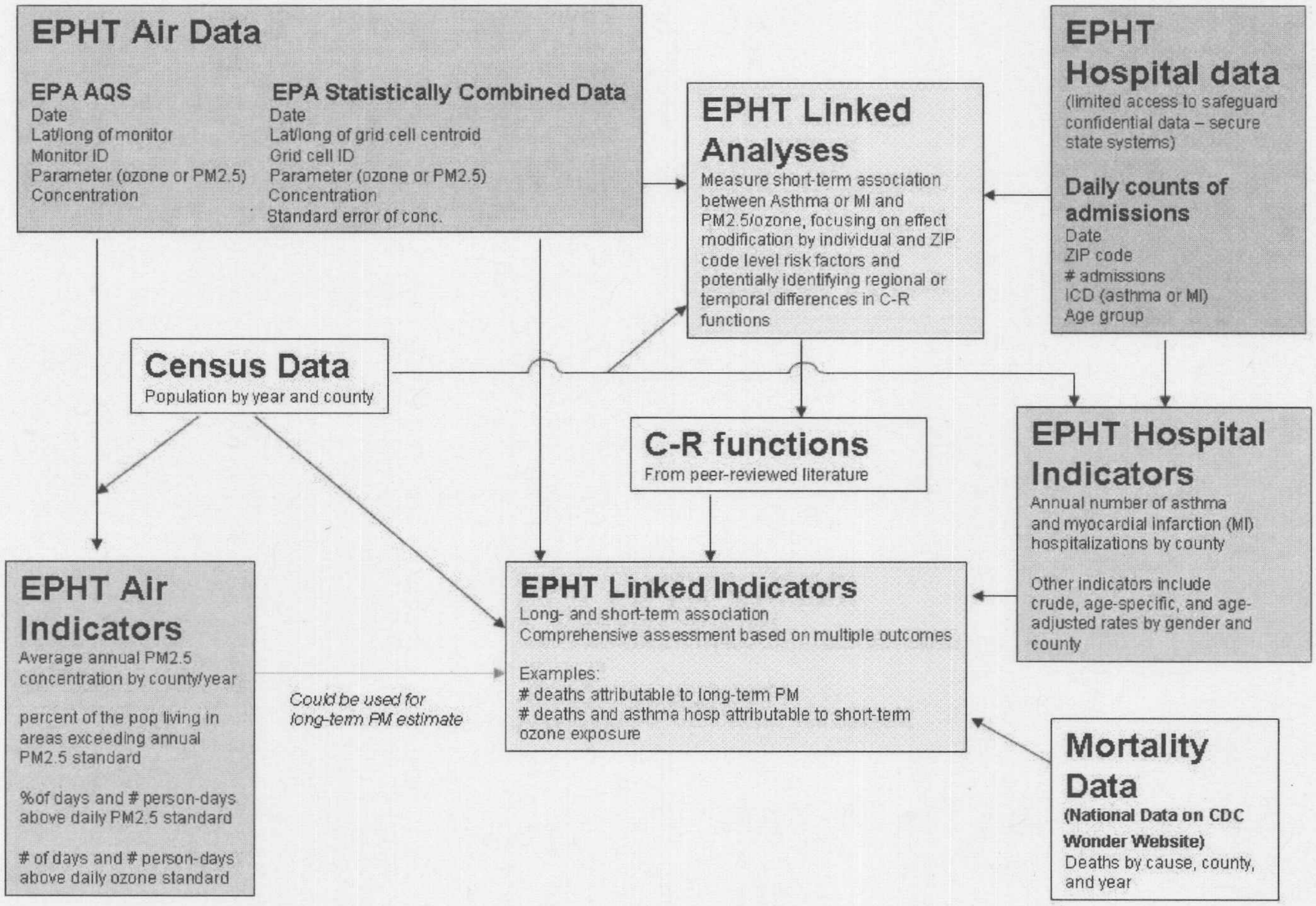
The environmental and health agencies at the state and national level will need to develop a system to facilitate the sharing and review of preliminary results before they are made widely available to the policy makers and the public. EPHT states will need to work together with experts to review analytic results when health impacts are updated. Currently there is no up-to-date system in place to easily share and combine the results of analyses in a central repository. In addition to a physical network, there is a need to develop a more robust network of professionals to review and integrate results from different sources.

Table 1: Comparing advantages and disadvantages of the EPHT air quality data

Factor	Ambient Monitor Data	Statistically combined data
Timeliness of data	3- 6 months after the monitor year. State and local agencies are required to submit their air quality monitoring data into AQS by the end of the quarter following the quarter in which the data were collected. These data must be certified by these agencies by June 30 each year (for the previous year) – within 1.5 years of the model year.	Each year of statistically combined data will be available within 2 years of the model year. There is a large computational and technical burden to producing the CMAQ estimates. Then it requires 3- 4 months to compute and check the statistical predictions, and statistical expertise to ensure that proper modeling assumptions and procedures have been used, and the results are reasonable.
Accuracy	The most accurate characterization of the concentration of a given pollutant at a given time and location. Measurements are based on nationally consistent methods including State precision and accuracy evaluations.	Improved estimates of pollutant concentrations (and uncertainties) at times and locations where they are not measured compared to CMAQ model. Accuracy near monitors is better than accuracy where there are no monitors.
Spatial coverage	Spatial gaps, especially for rural areas, since the monitoring network is mostly population-based.	Data will be provided on grid: 12 km in Eastern US and 36 km in Western US. No spatial gaps.
Temporal resolution	Varies by pollutant and location. ozone is monitored daily, but for most locations only during the ozone season (approx. April through October). $PM_{2.5}$ is often monitored year round using the Federal Reference Method (FRM). $PM_{2.5}$ FRM daily measures are often only available for every third day. Some continuous $PM_{2.5}$ monitors report daily $PM_{2.5}$ measurements on an hourly basis and have been converted to the FRM-like measures within AQS.	Daily estimates with no temporal gaps except for the first and last day of the year. (end effects of the model).
Ease of use	Medium – users must deal with missing values in space and time. EPHT must use consistent methods for handling missing values and developing exposure regions around monitors.	Easy - there are no missing values in space or time so the data will be used consistently in a national analysis.
Quality control	The data are supported by a comprehensive quality assurance program, ensuring data of known quality.	The quality of the predictions may not be consistent depending on the quality of the CMAQ estimates across states and may change as the data and methodology are improved over time. This information needs to be clearly documented for data users.

Figure 1: relationship between datasets and indicators

ANNEX B


EPHT Air Data
EPA AQS
Date
Lat/long of monitor
Monitor ID
Parameter (ozone or PM2.5)
Concentration
EPA Statistically Combined Data
Date
Lat/long of grid cell centroid
Grid cell ID
Parameter (ozone or PM2.5)
Concentration
Standard error of conc.
EPHT Linked Analyses
Measure short-term association between Asthma or MI and PM2.5/ozone, focusing on effect modification by individual and ZIP code level risk factors and potentially identifying regional or temporal differences in C-R functions
EPHT Hospital data
(limited access to safeguard confidential data – secure state systems)
Daily counts of admissions
Date
ZIP code
admissions
ICD (asthma or MI)
Age group
Census Data
Population by year and county
C-R functions
From peer-reviewed literature
EPHT Hospital Indicators
Annual number of asthma and myocardial infarction (MI) hospitalizations by county
Other indicators include crude, age-specific, and age-adjusted rates by gender and county
EPHT Air Indicators
Average annual PM2.5 concentration by county/year
percent of the pop living in areas exceeding annual PM2.5 standard
%of days and # person-days above daily PM2.5 standard
# of days and # person-days above daily ozone standard
Could be used for long-term PM estimate
EPHT Linked Indicators
Long- and short-term association
Comprehensive assessment based on multiple outcomes
Examples:
deaths attributable to long-term PM
deaths and asthma hosp attributable to short-term ozone exposure
Mortality Data
(National Data on CDC Wonder Website)
Deaths by cause, county, and year

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ANNEX B6.

Wartenberg D. It's up in the air: Some guidelines for Communicating air quality health impact estimates and their limitations to stakeholders.

ANNEX B

Daniel Wartenberg
August 12, 2008

It's Up in the Air:
Some Guidelines for Communicating about Ambient Air Quality

One of the most important goals of CDC's Environmental Public Health Tracking Program (EPHT) is to effectively and efficiently communicate information about ambient air quality, both in terms of the estimated potential public health impact on the general and highly susceptible populations, and the variation from place to place and over time. Indeed, one goal of any surveillance or screening program is to develop data and information appropriate for the design and implementation of useful interventions. Typically, these interventions will be implemented only if their relevance and impact can be conveyed clearly and convincingly to policy makers, the people responsible for implementation and those likely to be affected by the intervention.

In the case of ambient air quality, data are collected routinely from monitoring stations throughout the US, compiled and interpreted by local, state and federal officials, and usually made freely available on the internet. The goal of this paper is to describe some of the considerations in how the data are presented when made available, and to suggest considerations and strategies to make those presentations interpretable by the wide range of audiences interested in them. For the purposes of this paper, the discussion is based on consideration of two air pollution constituents, ozone (O_3) and particulate matter ($PM_{2.5}$), as well as estimates of population health impact.

One report that specifically addressed this issue broadly and relatively comprehensively, was developed for APHEIS Project, the Air Pollution and Health: A European Information System.(APHEIS 2004) The researchers noted differences between potential audiences, in terms of goals, scientific background, and culture, suggesting the need for information to be presented in a variety of formats, including a non-scientific publication format, to be accessible to those audiences. It is common knowledge that people learn in different ways: visual, verbal, reading, doing, interacting, etc. Older people rely more on affect (emotions, reactions, memory triggers) and younger people on cognitive skills. Therefore, the messages always have to be multi-modal. This paper draws heavily from the APHEIS Report and more generally from the knowledge generated throughout the repeated observations by psychologists, educators and social scientists who observe how people learn.

At the outset, it is helpful to identify key issues that warrant consideration: (1) goals of the communication; (2) intended audience(s); (3) types of information to be used and/or conveyed (e.g., emissions, monitoring observations, health impacts, indicators); (4) scoping issues (e.g., geographic and temporal scale); (5) health effect measures (e.g., acute vs. chronic effects, body counts vs. life expectancy vs. quality of life, health care costs); (6) major substantive messages (e.g., what people can and should do, general information, trends, regulatory violations, health alerts); (7) vehicles through which to convey information (e.g., scientific papers, reports, press releases, websites—text and graphics, newsletters or other periodic communications, and presentations; and, (8) factors that affect perception of and behavioral reaction to this information (e.g., local vs. more broad-based data). In addition, given the vagaries and idiosyncrasies of human populations, it is important that there be on-going evaluation of the transmission of the communications, its reception by the intended audiences and others, and their reaction, interpretation and planned responses. In other words, one always should have an on-going assessment of how well the communication plan is or is not working. I consider each issue, in turn.

<u>(1) Goals of the Communication</u>: There can be as many goals as there are distinct audiences and issues to be addressed. These would include, for example, identifying data needs for the underlying purpose of the monitoring, trying to help the audience understand the main scientific and health issues of concern, if not the details, providing a context for comparing risks/hazards for potential policy development or funding decisions, and possible implementations, prompting individuals or communities to change behaviors or actions to reduce pollutant levels and/or health risks, and possible some measure of the response to these messages, to provide feedback to those who were targeted to take actions. Messages may be crafted differently depending on which of the goals are most important. For EPHT, critical goals are to provide to a non-technical audience with information that conveys differences in health impacts attributable to variations in air quality at a regional or local level, for possible policy considerations and protection of public health, and suggestions for actions that individuals can take.

<u>(2) Intended Audience:</u> There are many intended audiences. While it might be most effective to develop separate messages for each audience, often this is not cost effective, although audience-specific messages can be developed and banked for future use. Therefore, it is important to look at the goals and locus of control of each audience to determine how best to group them in terms of targeting the messages. The APHEIS Project conducted a careful review of this issue for their study. Target audiences they considered include: government policy makers and those who influence them, media, environmental and health professionals, industry and transport sectors (pollution source managers and workers), health care providers, the public, and vulnerable populations. Each has a particular stake in this issue, as well as a different level of knowledge, experience and connection to the issues of health effects of air pollution. In addition, one should consider scientific professionals from non-health fields, such as physicists and atmospheric scientists, who may have extensive technical knowledge but less direct experience with the health effects attributable to exposure to air pollution. A further complexity in identifying audiences is that those with particular susceptibilities (e.g., children, the elderly, those with particular disabilities) may react more strongly to situations that directly affect their susceptibilities (e.g., people, with asthma or emphysema). So, great care should be taken crafting strategies to communicate with high risk populations.

Although all of these audiences have concerns about the health effects attributable to exposure to air pollution, each has different levels of concern, a different knowledge base, a different constituency and different primary goals. These differences can affect what individuals want to hear about, how they interpret the specific information provided to them, the degree to which they believe that the specific information addresses their concerns, and the technical level at which the information can be understood. For example, technical modeling results only rarely are appropriate for or understandable by most members of the public, but failure to provide details on model testing and validation to a scientist likely would raise concerns and doubts. In spite of the complexity, it would be most effective to have several different messages with the same general core content, each tailored specifically to each group, highlighting their specific interests, goals and expertise. Toward that end, APHEIS identified “four key objectives” that they apply to each audience: identify the information needs, assess how well APHEIS is meeting those needs, understand what is needed to better meet the information needs, and develop a communication strategy to do so. Initially, APHEIS decided to focus on one audience, government policy makers and influencers. We recommend a similar strategy for EPHT but suggest that the initial focus be slightly larger, including the public as well as policy makers and influencers, given that public access was one of the goals of the Pew Report(Pew Environmental Health Commission 2000) and the Congressional funders.

<u>(3) Types of Information:</u> There are several types of messages that one may wish to deliver to each of the audiences. For clarity, it is useful to determine specifically what type of information one wishes to convey, prior to focusing on the detailed content. Some possibilities include emissions data, ambient air monitoring observations, integrated/modeled emissions and ambient air data, suspected or observed health impacts, indicators (or combined summary measures) and the statistical uncertainties for each of these measures. Each measure has strengths and limitations. Direct monitoring data are viewed by some as the “gold standard,” because they reflect directly what is in the air we breathe. However, they are costly to collect, and tend to have limited spatial and temporal coverage. Emissions data reflect what is released to the environment, which is not directly relevant to exposures or health effects. However, these data can be used to model and estimate ambient levels of pollutants, and to do so at a higher spatial and temporal resolution than typically can be measured. The models which estimate emissions or ambient levels can be merged with and calibrated to limited measurements, validated, and used to predict or forecast values over larger space-time domains, while also providing estimates of uncertainty and precision. However, the results produced by models are sometimes seen as suspect, since they can be biased towards developers’ goals, and those biases, which may be unintentional, can be difficult to identify, even for technical experts. Both models and monitoring data often are used for exposure evaluations and drive the health concerns.

Health impacts focus on the public health consequences of exposure to ambient air pollutants. Generally, this is of greater concern than the exposures themselves, but may be harder to assess, can involve multiple risk factors only some of which are air pollutants, and may take years to decades to manifest themselves. Further, individuals with existing health conditions sometimes are more susceptible and respond to lower levels of and in a more extreme manner to the same exposures as healthier members of the public. Impacts on individuals also can be mediated by other factors, such as the presence or absence of air conditioning. Rather than relying on direct measurement of health effects, models can be used to estimate or project health effects, but also are subject to concerns of appropriateness, accuracy, reliability and validity, not to mention interpretability. Finally, there are indicators, which are summary health or exposure measures, which typically provide space-time averages. These can be perceived as more limited in that generally they do not provide same resolution and variability as direct measurements but are much simpler in concept, construction, and interpretation. Assessing the uncertainty variability and uncertainty in indicators can be quite difficult.

One also might want to report regulatory compliance information, whether or not, and how often, levels meet or exceed specified standards or levels at which they are anticipated to cause health effects. These relate to regulatory requirements rather than to health impact, but often regulations are designed to prevent health impacts and thus may be useful in addressing the underlying concerns. Compliance data relatively easy to report but contain less information than most of the measures mentioned above.

(4) Scoping Issues: Another important consideration in developing a communication strategy is determining the most appropriate space and time scales with which to report the data and effects. Often, more than one may be appropriate. For example, one may want to use a national map for context, but then provide insets of areas of particular regions or localities of interest or concern. Similarly, with time, one may want to provide data portraying long-term trends (e.g., weekly, monthly or yearly), but also show short term variability (e.g., daily or hourly) when the amount and rate of change of air pollutants is greater, such as for Summer months. It may be particularly helpful to include for some of the measures the space-time scales that are used by some of the standards and regulations, such as particular averaging times for reporting air pollutants. For example, ozone of is reported based on one-hour and eight hour averaging times, but one might also want to consider daily, weekly, monthly, seasonal and annual averages. One also needs to explain what “averaging time” means. Again, decisions for the space-time scales likely vary according to the audience one is trying to reach, the particular questions of concern, and the audience’s degree of technical background. Some testing of the audiences' goals and appreciation of different space-time scales may help immeasurable in designing effective communication.

(5) Health Effect Measures: There are various considerations necessary in reporting on health effects. First, one has to determine the type of effect one wishes to evaluate, for example morbidity (e.g., breathing problems) vs. mortality (e.g., death), and acute (e.g., myocardial infarction) vs. chronic (e.g., lung cancer) end points, depending on the nature of the particular concern. One also needs to decide whether to report for the whole population, the most sensitive subgroup (e.g., those with active lung disease), or those of greatest concern to the larger population (e.g., children). Within each of these realms, one also needs to consider what information is most useful and/or interpretable. For example, for a long time, researchers reported the number of deaths attributable to air pollution (i.e., the body counts) as the most striking formulation. However, more recently researchers have begun to consider more detailed aspects of impact, such as not simply whether someone is thought to have died prematurely from air pollution, but also how prematurely they died (i.e., how may years early) or years of life adjusted for disabilities (DALYs) or quality (QALYs) and other types of Health Adjusted Life Years (HALYS). Some question the validity of these more detailed measures, while others argue they better capture people's feelings and experiences (McMichael, Anderson et al. 1998; Gold, Stevenson et al. 2002; Arnesen and Trommald 2004; Brunekreef, Miller et al. 2007) Another measure, of particular interest to policy makers, is the health care costs likely to be incurred (or saved) as the result of changes in the levels of air pollutants, both with respect to an individual and a population. Choosing among these often depends on the audience, the context, the particular pollutant of concern, the characteristics of the population under consideration, and the intended use of the data.

(6) Major Messages: In developing messages for a communications program, one must be clear about what message one wishes to deliver, and what response one would like to elicit. For example, the objective may be to provide the community with information about the environmental status of their community. There may not be clear data available on health effects, but they are likely to appreciate changes or trends in background levels of certain substances so that when health effects data become available they will have a context from which to compare their community with others. Or, the goal may be to provide information about hazards they are likely to encounter, small though they may be, and let the community decide how they want to respond to them. In more serious pollution situations, with compounds of known health consequences, the objective could be to encourage individuals to take personal actions to limit exposure, and the community to advocate for political action because they are being affected disproportionately. Providing context about regulatory compliance may be helpful, so that they can decide whether or not action or mitigation is appropriate and/or necessary, and if the current regulations are sufficiently protective, in their view. Finally, helping people understand the meaning and implications of air pollution alerts, and the benefits of behavior changes can lead to reductions in exposures through changes in personal behaviors and well as more broad-based actions. All of these options require careful thought and consideration as they each have consequences, as does failure to alert people to these issues.

(7) Vehicles through which to Convey Information: One of the most critical considerations in any communication strategy is how to present the information in a manner that is clear, comprehensive, accurate, precise, understandable and relevant to the concerns at hand, with some indication of reliability or uncertainty. At the outset, the APHEIS report(APHEIS 2004) suggests that it is important that scientific papers be available as primary sources as well as back-up and/or support for communications. They suggest that communications should include a variety of vehicles, including complete scientific reports, summary scientific reports, peer-reviewed scientific papers, brochures with a policy focus, PowerPoint presentations with a scientific focus, PowerPoint presentations with a policy focus, Q&As/FAQs with a scientific focus, Q&As/FAQs with a policy focus. They also suggest that presentations should include, "a few key messages presented simply and clearly in easy-to-understand terms, using bullet points and supported, when appropriate, by simple graphs, charts and/or tables." One of their respondent groups suggested that, "reports should use simpler language, and more boxes, graphs, maps and colors."

We strongly believe that the use of simple, clear maps, charts and graphs can be among the most effective ways to present information, and make it relevant to audiences. However, it requires substantial work to achieve an acceptable standard for these displays to useful and convey the appropriate information, and these displays may be supported by a small of bullets highlighting key features, a brief narrative or discussion, and suggestions for where to get more information.

A substantial literature documents many of the mistakes that have been made in developing displays(Tufte 1990; Monmonier 1997; Tufte 2001), and presenters must be careful not to repeat these mistakes, both for credibility and to be effective communicators. There are well researched methods that can be used to make effective displays, from using understandable color combinations on maps, even for audiences with colorblind members, (www.colorbrewer.com) and to using formats that highlight specific aspects of the display.(Bell, Hoskins et al. 2006) One asset of maps is that viewers usually like to identify the area where they live, as a way a validating one aspect of the display. Maps often make people feel more comfortable than do scientific charts and tables because we all are used to reading road maps and have experience interpreting features and patterns on them. The perception of familiarity and simplicity makes them particularly good and effective vehicles for communication. Yet, maps that try to present too much information and require cognitive reasoning based on multiple pieces of information derived from maps can frustrate users and block the intended message of the communication. This is an approach that requires special attention to detail, and in depth review by both technical and non-technical staff, and ideally a small sample of the intended audience.

Figures 1-8 demonstrate some of the strengths and weaknesses of displays. These examples were not chosen because they are particularly good or bad examples. Rather, they are chosen to show that even the best displays have limitations or weaknesses and even the worst displays have strengths and can convey important information. They are provided to show some real world examples from which we can learn, copying features from some, and modifying our displays to avoid problems with others.

Figures1 and 2, taken from EPA websites, display two aspects of air pollution information. Figure 1 shows the trend in time of air pollution with a measure of variability across sampling sites. However, from this simple and easy to interpret graph, it is not possible to infer where the sample sites are, whether the high areas are close to one another, nor how variable each individual site is (i.e., is the variability due to consistent differences among the same sites, each of which is fairly stable, or are all sites highly variable, and in an unpredictable pattern?)

Figure 2 depicts areas of regulatory attainment within one of EPA nine administrative regions. As with Figure 1, this map conveys a relatively simple message but without much outside context. For example, it does not address the stability of the pattern depicted, at what scale is it evaluated, are there any short, medium or long term variations that increase, decrease or change the locations of the non-attainment areas. Perhaps a series of seasonal or annual maps would help clarify this, or inclusion of a small time trend plot for one of the areas.

Figure 3, from the APHEIS Project, has a more complex message, providing comparisons across a number of cities and also showing the impact of, but not describing on the graph, data adjustments. This was targeted for a more technical audience, for whom it conveys a wealth of information about two different pollutant measures, their geographic and statistical variability, their comparability or correlation. For the public, it might display useful information about a particular city, and how it compares to the others, but the complex of lines may make it more difficult to decipher. It would be helpful to know in a few words in what way were the PM_{10} values corrected, and how and from what were the $PM_{2.5}$ values computed. The title does explain that the data are annual. It is interesting that for variability or uncertainty the 5th and 95th percentiles are shown along with the central tendency, but it is surprising that the central tendency is not analogously the central distributional value (i.e., the median) but rather the arithmetic mean. While the names of the cities are provided, an inset map of the locations of those cities would make the graph more generally accessible for comparing among cities and assessing whether there are broad, regional patterns, possibly suggesting transport mediated effects, or much variation among neighboring cities, suggestion effects due to local sources.

Figures 4A and 4B show considerations that must be addressed in mapping: whether to adjust mapping areas to reflect population characteristics (e.g., using a cartogram) and the scale of data display or averaging, which can result in different interpretations from the same base data. Figure 4A is a choropleth map that shows reported percentages for each geographic unit (state) based on its true geographic boundaries. The values are grouped by color into six ordered categories for simple evaluation. However, because the data reported only are percentages, one has no idea whether in a given state they represent 1, 10, 100, or 10,000,000 voters. Figure 4B shows a cartogram of the same data, with the identical color coding for each state, but the area of the state is scaled to the size of the states' population, while also trying to maintain its approximate shape for recognizability. Note that given our current voting system, the choropleth map is more relevant for Electoral College voting (all of each state's electoral votes are awarded to the candidate that has the most votes within that state), while the cartogram is more relevant for the popular vote (each individual vote is awarded to the candidate chosen, irrespective of the votes of others in a given state).

Figure 5 shows the impact of the spatial scale of the data on patterns and interpretation. For an evaluation of housing age, we obtained US Census housing age data at the census block group level, and mapped them as obtained. Next, we combined the values for all the block groups contained within a zip code and mapped these data. Finally, we combined values for all the block groups within a county and mapped these values. Note that even a cursory visual examination shows markedly different patterns, although the most broad-scale patterns remain.

Figure 6 shows a plot that demonstrates the association of two variables, demonstrating how removal of lead from gasoline, a policy intervention, is associated with decreasing childhood blood lead levels, a health effect measure. This approach is most appropriate for EPHT "data linkage" studies. It would have been helpful if the figure included information about the number of children upon which the graphs are based, to describe the statistical variability of the numbers, as well as some of the demographic characteristics of the children, to help with interpretation and applicability to subpopulations. However, much of this information is available in the reference that is listed in the figure.

Figures 7 and 8 are examples of a very rich but complex display method called linked micromaps. Due to their complexity, these are more appropriate for technical experts rather than the general public. What this formulation does is: (a) display the central value and 95% confidence interval for two specified measures, separately, allowing for comparison of their values across all 50 states; (b) shows the association of these two measures by plotting the measures for the same state next to each other; and, (c) shows the geographic context of these data by highlighting similar values in the adjacent map, that shows in color small subsets of states that have similar values, states that have greater values for the primary (left most) measure, showing on the map higher values in white and lower values in grey.

For specific messages, one needs to determine what is of greatest importance, and the identification of the graphic approach that highlights this most effectively. One particularly important aspect of these plots is that they show confidence intervals for the central values for each geographic unit. I do not know of any method that shows clearly the geographic distribution of confidence intervals, and particularly not for two variables simultaneously. The issue of confidence intervals, and uncertainty, is an important issue to address, but one that often gets overlooked in mapping applications.

Finally, one may want to consider various modes of transmission of the information, from print (e.g., fact sheets) to electronic (e.g., web pages) to oral (e.g., public service announcements), how to balance descriptive information with quantitative information and graphics, and whether displays should be static or interactive. These all have advantages and disadvantages. The specific application of linked micromaps shown here is from an interactive, public website maintained by the National Cancer Institute. One could develop a similar venue for various air pollutants and demographic characteristics national, at the county level.

(8) Factors that Affect Perception of this Information:

A substantial amount of research has been conducted on the issue of what factors external to a presentation or display affect the perception of the information depicted, to help guide those wishing to effectively communicate specific information or messages. For example, investigators have considered what is heard in presentations and how people react to it based on the characteristics of the audience, such as gender and race(Johnson 2002; Johnson and Chess 2003) as well as the local context of the problem(Bickerstaff and Walker 1999; Bickerstaff and Walker 2001; Howel, Moffatt et al. 2002) and other factors. Other investigators have considered the formats in which the data are presented, such as the Pollutant Standards Index (PSI)(Johnson 2003), and the utility of comparisons to existing standards or benchmarks.(Johnson and Chess 2003) Some investigators have looked at whether such information is likely to result in changes in personal behavior.(Skov T., Cordtz T. et al. 1991) Still others have studied the ways the public links air pollution to health effects.(Howel, Moffatt et al. 2003) Depending on one's purpose, one might want to use this information in guiding the structure and content of a presentation. One way to address this most directly is, when designing indicators for the public, to work directly with the public.(Elliott, Cole et al. 1999) After all, they ought to be the best gauge of what they want to know, and how well the message is being delivered.

In addition, one must consider the structure, format and content of presentation and display. As noted above, issues including text vs. graphs vs. maps are important, as well as the style, color, geographic and temporal scope. Perceptions may differ if the material presented is spoken, if it includes visual aids (e.g., graphs or maps), if there are handouts available during and/or after the presentation that summarize or explain further the main points that are presented. Again, what approaches work best varies greatly among audiences.

Evaluation:

The only way to be sure that the desired message is both believed and received as desired is to evaluate whether the desired audience has gotten and understood the message. Approaches for doing this efficiently and effective are complex and should be the subject of a separate essay. However, without this direct validation, one cannot be sure that one had done an adequate job in conveying the information. This evaluation should involve some members of audience so that they can articulate clearly from the perspective of those affected, what is needed, what worked in this specific context, what didn't, and why. This should help researchers better understand the process and how to improve their efforts over time and across multiple audiences.

Final Recommendations:

From this overview of issues in the communication of air pollution and health impact data, it is clear that research is limited, approaches used vary widely, and interpretations differ both within and between methodologies. As both concerns and interest grow, it is important that additional research be conducted to better understand how to identify the best strategies to communicate the desired messages and engage audiences, and how to evaluate the effectiveness of the communication approaches.

Acknowledgements:

ANNEX B

I thank Dr. Michael Greenberg for providing comments on this manuscript, and other EPHT researchers for providing feedback. This work was supported by cooperative agreement U19 EH000102, from NCEH, Centers for Disease Control and Prevention

ANNEX B

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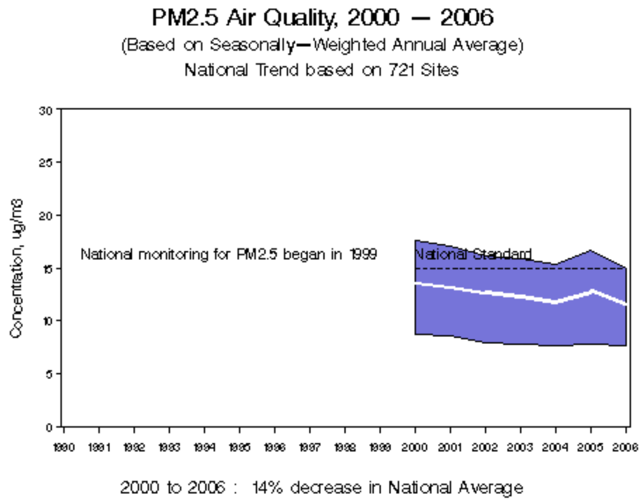
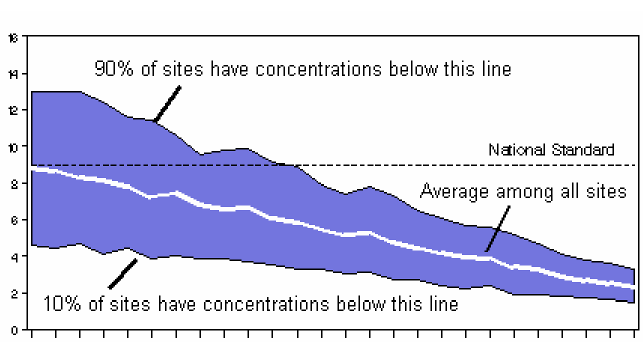
Figure 1: USEPA: Trends in $PM_{2.5}$ (http://www.epa.gov/air/airtrends/pm.html)



National Trends in Particulate Matter Levels

Using a nationwide network of monitoring sites, EPA has developed ambient air quality trends for particle pollution, also called Particulate Matter (PM). Trends from 1990-2007 are shown here for PM2.5 and PM10. Under the Clean Air Act, EPA sets and reviews national air quality standards for PM. Air quality monitors measure concentrations of PM throughout the country. EPA, state, tribal and local agencies use that data to ensure that PM in the air is at levels that protect public health and the environment. Nationally, average PM concentrations have decreased over the years. For information on PM standards, sources, health effects, and programs to reduce PM, please see www.epa.gov/air/particlepollution.

How to Interpret the Graphs



The blue band shows the distribution of air pollution levels among the trend sites, displaying the middle 80 percent. The white line represent the average among all the trend sites. Ninety percent of sites have concentrations below the top line, while ten percent of sites have concentrations below the bottom line.

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Figure 2: USEPA Region 9: Ozone Attainment Areas
(http://www.epa.gov/region9/air/maps/r9_o3.html)

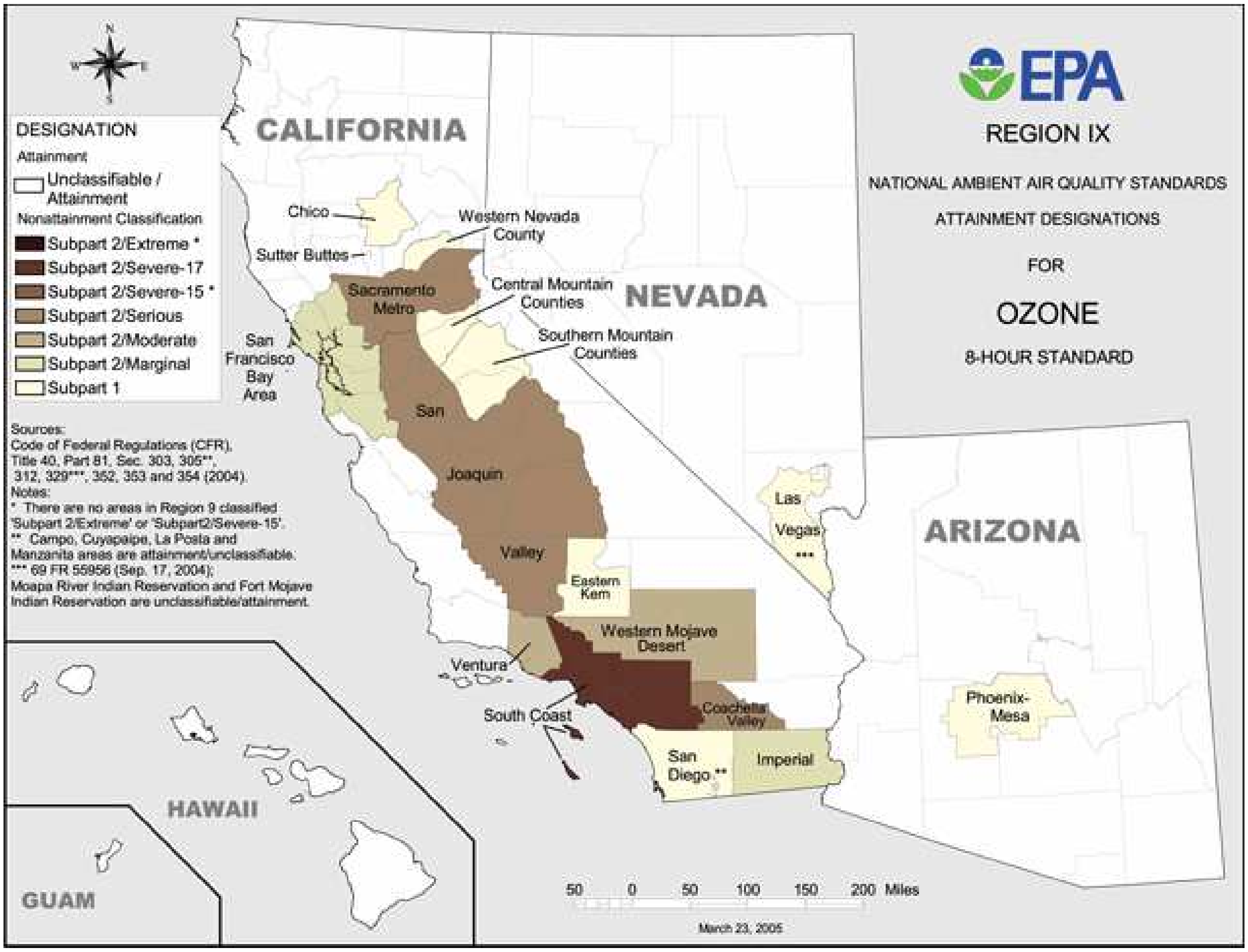

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Figure 3: APHEIS Sept. 2006

Apheis 3: HIA of long-term exposure to PM2.5 in 23 European cities (http://www.apheis.net/)

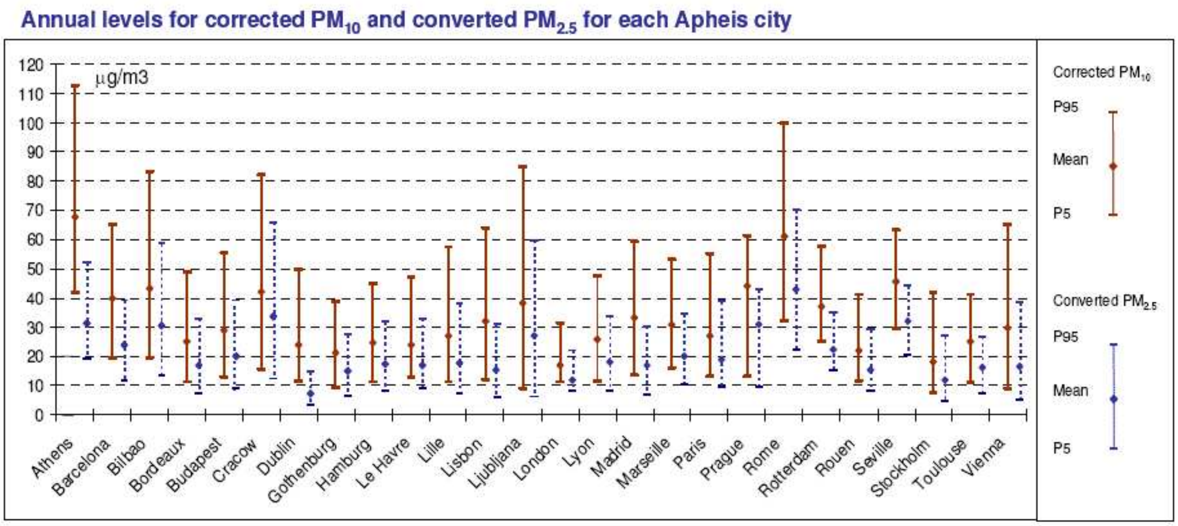

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Figure 4A: A Choropleth Map of Voting Percentages

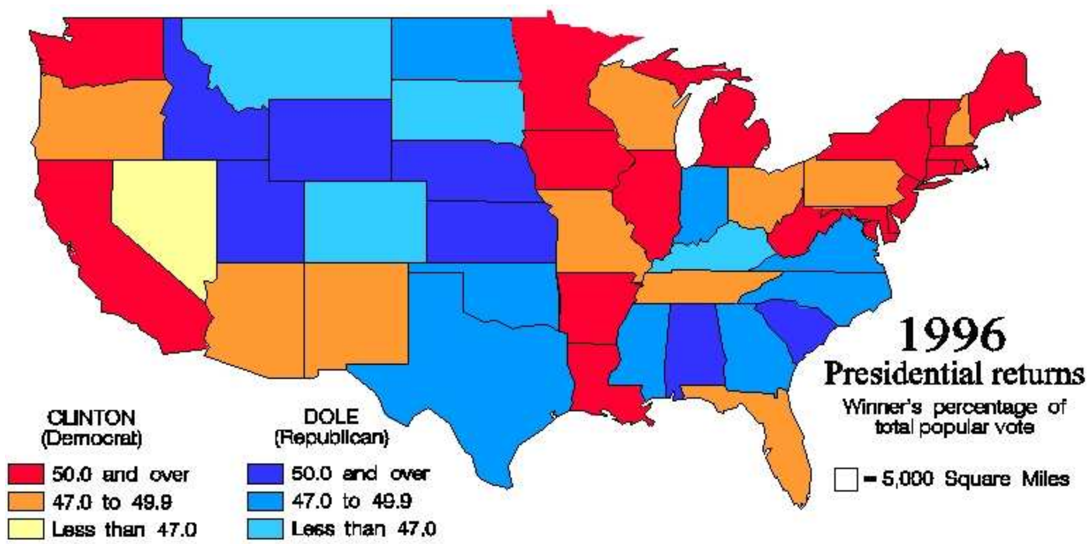

Figure 4B: A Cartogram of Voting Percentages

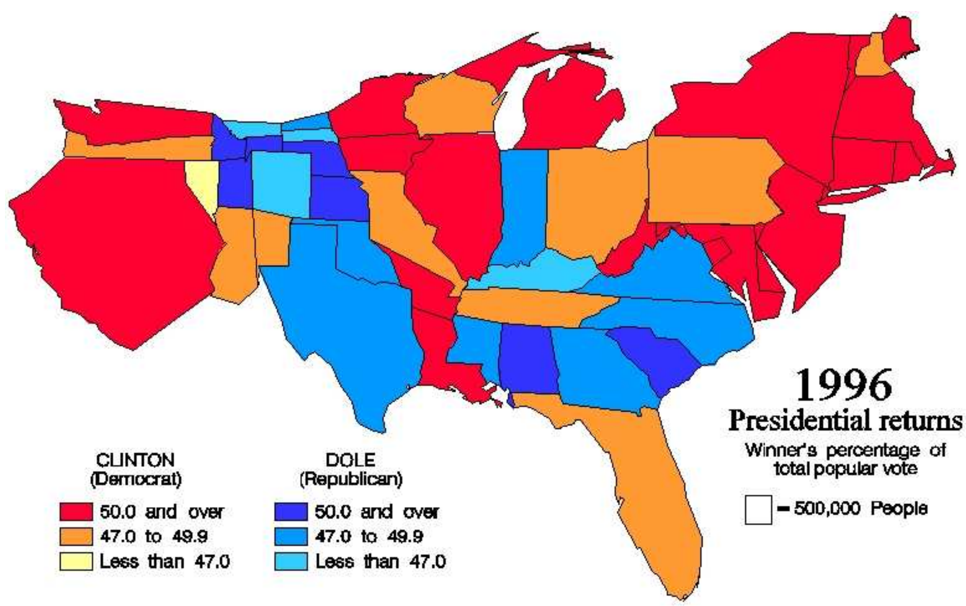

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Figure 5: Comparative Maps of the Same Data at Different Spatial Scales (Elliott and Wartenberg 2004)

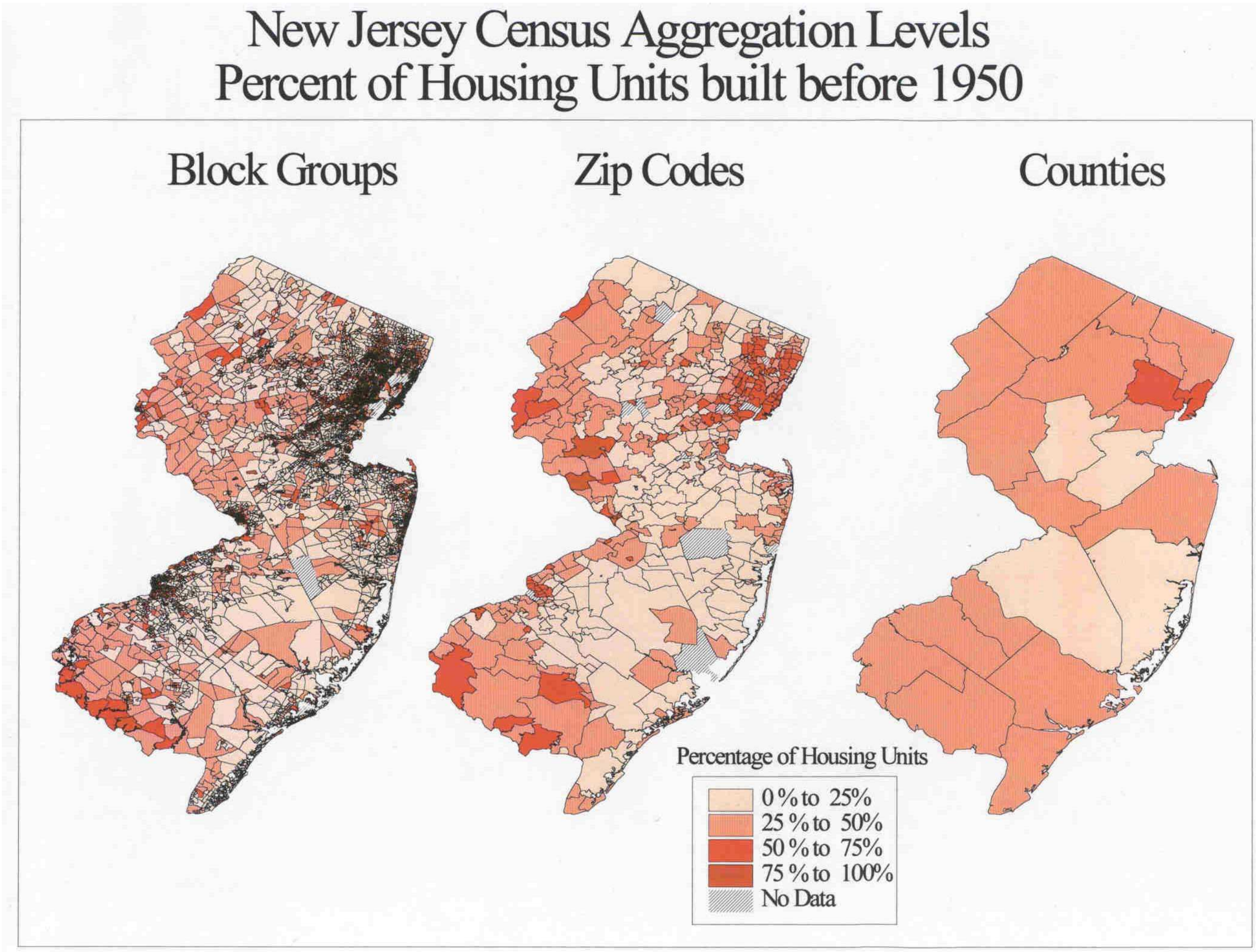
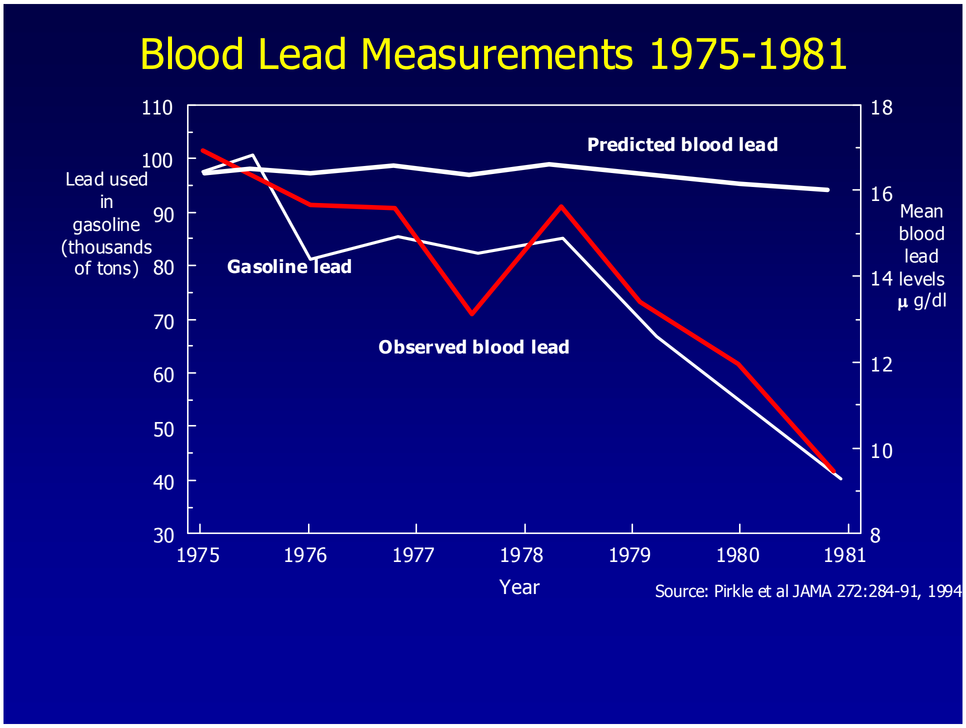


Figure 6: The Impact of Removal of Lead from Gasoline—A Data Linkage Display(Pirkle, Brody et al. 1994)



ANNEX B

Figure 7: Linked Micromap Sorted by Exposure(Carr, Wallin et al. 2000; Carr 2001; Bell, Hoskins et al. 2006)

(http://statecancerprofiles.cancer.gov/micromaps/)

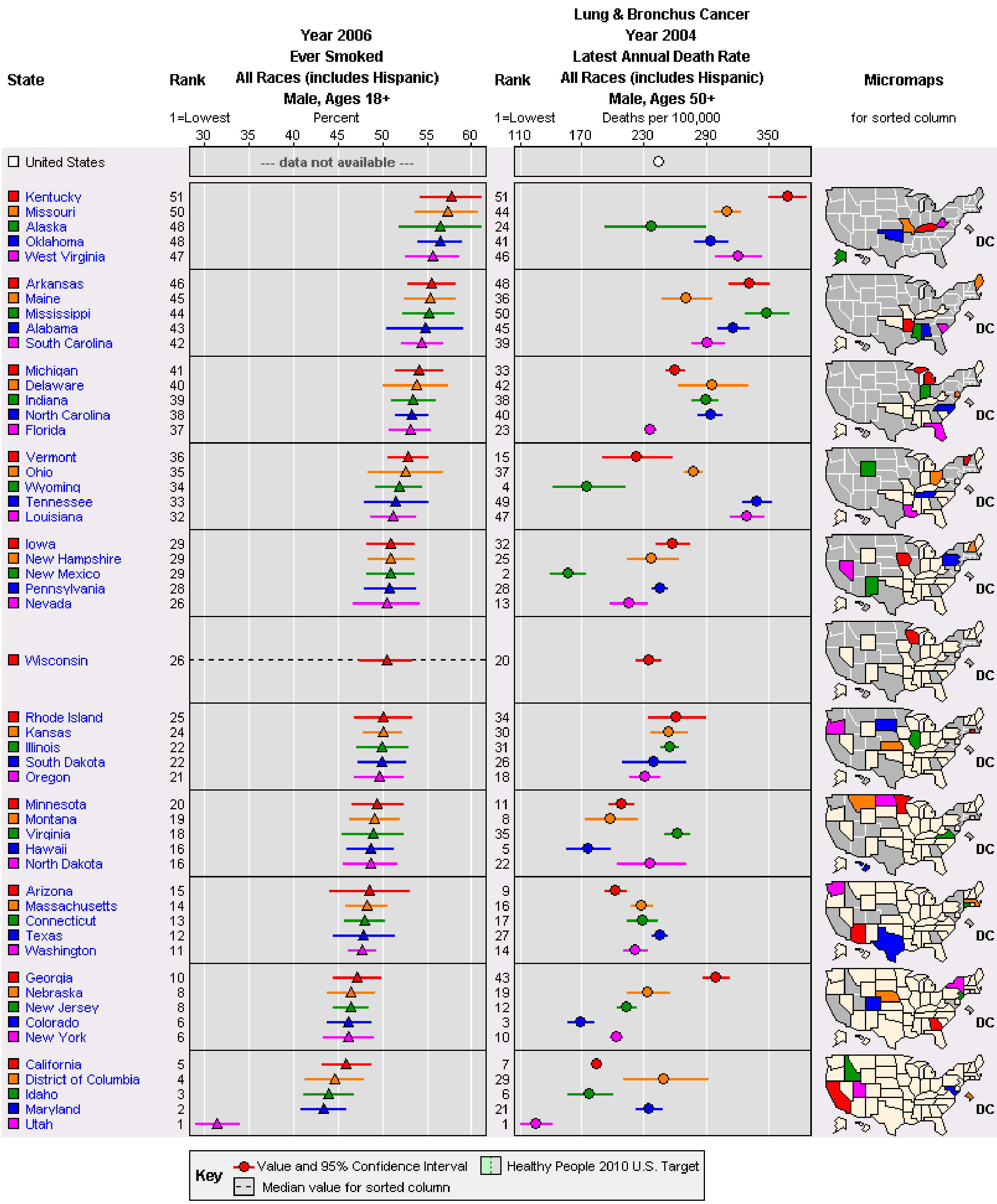


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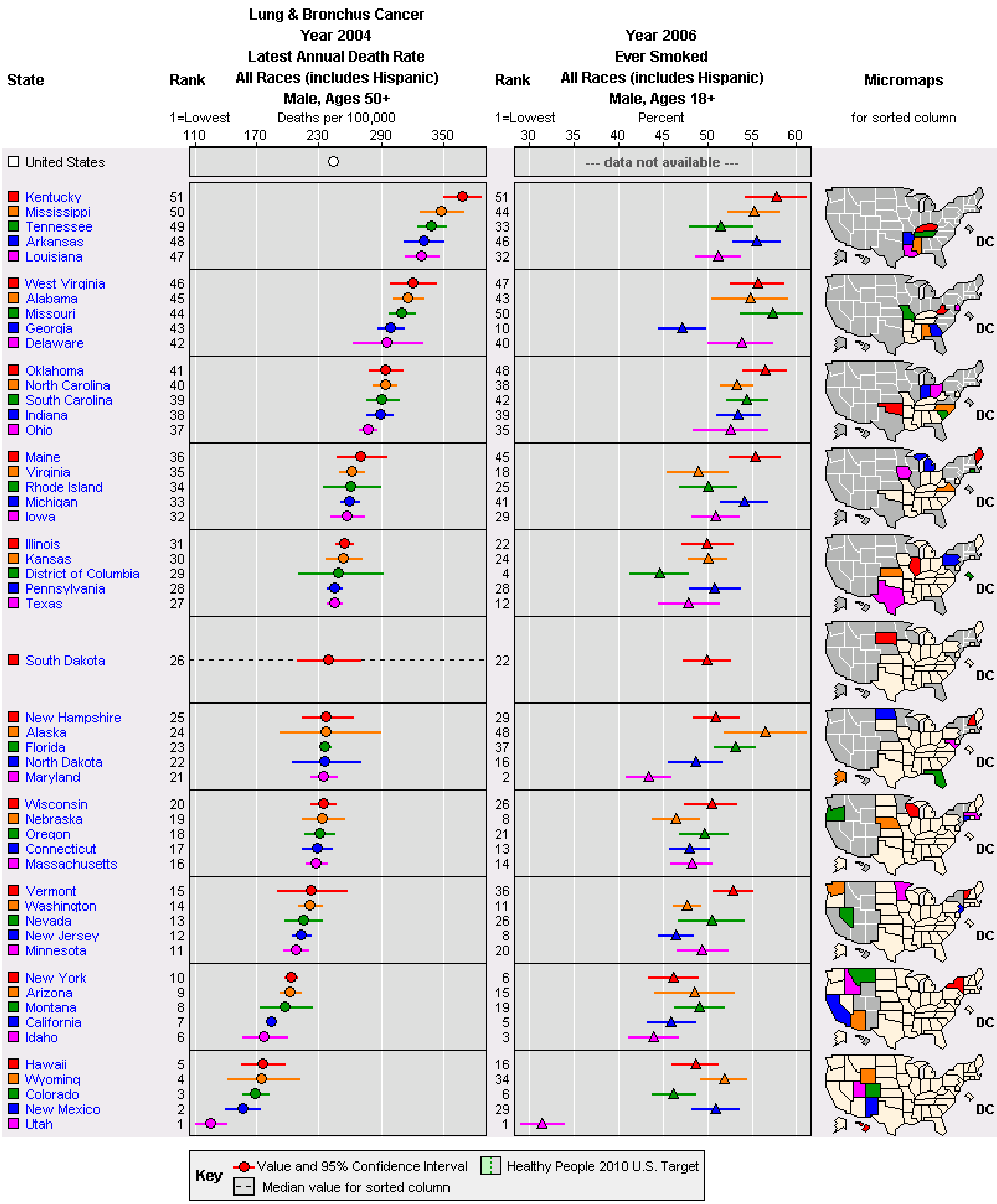
Figure 8: Linked Micromap Sorted by Mortality Rate(Carr, Wallin et al. 2000; Carr 2001; Bell, Hoskins et al. 2006) (http://statecancerprofiles.cancer.gov/micromaps/)



ANNEX B7.

Medina S, Le Tertre A, Sklad M. The APHEIS Project: Air Pollution and Health – A European Information System.

The Apheis Project
Air Pollution and Health - A European Information System

www.apheis.org

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Introduction

The Why: What's the problem we face?

Air pollution continues to threaten public health

Numerous studies and the lack of effective policies reveal that air pollution continues to threaten public health in Europe today. As but a few examples:

1. A study (Künzli et al., 2000) published in The Lancet revealed that roughly 40,000 people were dying every year from the effects of air pollution in three European countries alone, costing them some €50 billion annually (Sommer et al., 2000).

2. The Cost-Benefit Analysis of CAFE (Clean Air For Europe) (2005) estimated:

- 3.7 million years of life lost each year (based on the year 2000) associated with current exposure to PM2.5 across the European Union's 25 countries
- Or 348,000 estimated premature deaths in Europe every year
- 100,000 cases of respiratory or cardiac hospital admissions
- 30 million respiratory medication use days
- Several hundred million restricted activity days each year

3. On December 12, 2007, according to its press release, "The European Parliament adopted a second-reading legislative report which provides the maximum concentration levels for PM2.5. The report is the basis of an agreement with the Council on a directive on air quality (CAFE Directive)."

Commenting on the proposed CAFE Directive, scientists had previously said, "As it stands, this new Directive would mark a serious reduction in public-health protection from air pollution within the Member States, with health impacts amounting to thousands of premature deaths per year." (Declaration on Need for Stricter European Regulation of Air Pollution, ISEE-ISEA and IRS Munich and Paris, September 4, 2006).

Key users still lack vital information

Before the Aphea research program began in 1993, European policy makers who directly influence the reduction of air pollution and its impact on health relied mainly on American research for their information. This was because little European data was available. They also relied on individual studies that did not use common methodology. As a result, they could not compare research findings and draw synthetic conclusions.

The Aphea program (Short-term Effects of Air Pollution and Health: A European Approach) solved these problems by providing new, reliable European research data on the effects of air pollution on public health; and by instituting a standardized, common methodology across different countries (Katsouyanni et al., 1996, 2001)

However, being limited in time, Aphea was not designed to provide information for environmental-health professionals on an ongoing basis.

In addition, policy makers, healthcare providers, patient organizations and the general public lacked both information on the impact of air pollution on health and the communications tools that deliver that information to them, all tailored to their specific needs.

The What: How did we propose solving the problem?

Given this situation, we designed the Apheis program (Air Pollution and Health – A European Information System)[1] to expand knowledge and understanding among all these audiences of the impact of urban air pollution on health by providing them with an up-to-date, easy-to-use information resource on the subject. The goal remains to help them make better-informed decisions about the political, professional and personal issues they face in this area.

The How: Twenty-six centers across Europe gather and analyze information on an ongoing basis, and communicate it to key audiences

Apheis developed a public-health surveillance system (Teutsch et al., 1994) to provide information at regular intervals on the effects of air pollution on health tailored to the needs of its audiences.

For this purpose, Apheis built on previous, extensive experience acquired in France creating information systems on air pollution and public health:

• The ERPURS program (Medina et al., 1997), which has monitored the effects of air pollution on public health in the Paris metropolitan area since 1994

• The subsequent PSAS program, which began in 1997 (Quénel et al., 1999, Host et al, 2006).

The Apheis public-health surveillance system specifically:

• Quantifies the effects of air pollution on public health at the local and European levels

• Assesses the importance of factors that can influence concentration-response relationships

• Delivers standardized, periodic reports on the impact of air pollution on public health.

Apheis 1

During its first phase starting in 1999, Apheis achieved two key objectives:

• It defined the best indicators for health impact assessment (HIA) of the effects of air pollution in Europe. For this purpose, Apheis created five advisory groups in the fields of public health, health-impact assessment, epidemiology, exposure assessment and statistics. These groups drafted guidelines that defined the best indicators for public-health surveillance and provided standardized protocols for data collection and analysis.

• It identified those entities best able to implement the surveillance system in the 26 cities in 12 European countries participating in the program (Figure 1); understood how the different entities could work together on the local, national and European levels; and assessed each entity's ability to implement an HIA of particulate pollution using the guidelines drafted by the advisory groups (Medina et al, 2001).

Apheis 2

During its second phase, Apheis implemented its organizational model (Figure 2). Among other tasks Apheis also used its public-health surveillance system to conduct an HIA of PM10 and black smoke (BS), applying the above guidelines to gathering and analyzing pertinent data. For the HIA, Apheis provided all the centers with HIA methods and tools and a template for the city-by-city HIA reports.

This first HIA found between 544 and 1,096 "premature" deaths that could be prevented annually if, all other things being equal, short-term exposure to outdoor concentrations of PM10 were reduced by 5 $\mu g/m^3$ in Apheis cities. On the other hand, the expected benefits of reduction in mortality in the long-term were still greater. The HIA estimated that, all other things being equal, between 3,368 and 7,744 "premature" deaths could be prevented annually if long-term exposure to outdoor concentrations of PM10 had been reduced by 5 $\mu g/m^3$ in each city. Apheis published the findings of this work in its second year report (Medina et al, 2002) and in a scientific paper (Medina et al, 2004).

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[1] Apheis is co-funded by the Pollution-Related Diseases Program of the DG SANCO of the European Commission (contracts n° SI2.131174 [99CVF2-604], SI2.297300 [2000CVG2-607] and SI2.326507 [2001CVG2-602]) and participating institutes

Apheis 3

In its third phase, 2003-04, Apheis initiated the development of a communications strategy and updated its HIAs through its public health surveillance system.

Developing an Apheis communications strategy

"The DETR (UK Department of the Environment, Transport and the Regions) has had little success ensuring that anyone takes notice of the information provided." – Dr. Erik Millstone, Science and Technology Policy Unit, Sussex University

As already stated, the Apheis program seeks to meet the information needs of a wide range of individuals and organizations concerned with the impact of air pollution on health in Europe; and as a first step the needs of those individuals who influence and set policy in this area on the European, national, regional and local levels.

Like other providers of scientific information, however, Apheis had reason to believe that its many audiences, and this one in particular, were making little use of the scientific reports it produces.

To ensure it meets the needs of policy advisors and makers, Apheis decided to develop a communications strategy based on learning directly from its members this key audience's needs and the usefulness to them of the Apheis 2 report.

For this purpose, Apheis interviewed 32 individuals who influence or set policy on air pollution and health in the UK and Spain and who are active in the fields of public health and the environment.

Through this research Apheis sought to describe this audience's information needs as accurately as possible; and then produce recommendations for developing communications tools that would help the audience's members best understand, absorb, process and act on the information Apheis provides.

Our research showed in particular that (Figure 3):

• Policy advisors and makers are generally unlikely to use the scientific reports we develop as is, contrary to scientists

• A long, complex chain comprising many players leads from the scientists to whom we distribute our reports directly, and who use them, to the policy makers who ultimately have the greatest effect on public health, but who only receive our reports indirectly and use them rarely, if at all

• Each of our two audiences of scientific and policy users has different problems to solve, different levels of scientific knowledge and different cultures, and different ways of processing information for themselves and for pass-on users, meaning each audience has different information needs.

Based on this evidence, we concluded that Apheis needs to act proactively to:

• Apply this knowledge to the way it shapes and delivers its information and messages by developing a range of communications tools that goes beyond our comprehensive scientific reports to include summary reports, brochures, presentations and Q&As whose focus, content and form are tailored to the separate information needs of scientific and policy users

• Ensure that the information needed by policy advisors and makers actually reaches them.

Taking these steps should greatly enhance the way Apheis communicates with the key audiences that set policy on air pollution in Europe, and thus help Apheis contribute better to improving public health.

Update Health Impact Assessment

Tables 1 and 2 summarize the HIA scenarios performed in Apheis 3. Again, for the HIA, Apheis provided all the centers with HIA methods and tools and a template for the city-by-city HIA reports.

Key HIA findings

During Apheis 3, we updated the estimates of the effects of air pollution on health. We established new all ages respiratory concentration-response functions (C-R functions) suitable for HIA. We introduced methodological innovations to improve the estimated impacts of short-term changes in exposure to air pollution. And we calculated reduction of life expectancy, beside the absolute number of cases, to estimate the health impacts of long-term exposure to air pollution.

Apheis 3 revealed that in the 23 cities measuring PM10, totalling more almost 36 million European inhabitants, all other things being equal, if exposure to outdoor concentrations of raw PM10[2] was reduced to 20 µg/m^3 in each city, 2,580 "premature" deaths (including 1,741 cardiovascular and 429 respiratory deaths) could potentially be prevented annually if the impact estimation is limited to 2 days of follow-up. The short-term impact cumulated over 40 days was more than twice as large, amounting to 5 240 total deaths (including 3,458 cardiovascular and 1,348 respiratory deaths).

Long-term effects of pollution reduction were even higher. Our HIA estimated that all other things being equal, reduction of long-term exposure to corrected PM10[3] to 20 µg/m^3 in each city would result in prevention of 21,385 "premature" deaths annually.

Stated otherwise, for both total and cause-specific mortality, the benefit of reducing converted PM2.5[4] levels to 15 µg/m^3 was more than 30% greater than for a reduction to 20 µg/m^3. However, even at 15 µg/m^3, a significant health impact was expected. In terms of life expectancy, all other things being equal, if the annual mean of PM2.5 converted from PM10[4] did not exceed 15 µg/m^3 in the 23 cities measuring PM10, the expected gain in life expectancy of a 30-year-old person would range, on average, between 2 months and 13 months, due to reduced risk of death from all causes. An example of the impact in terms of life expectancy in Seville is shown in Figure 4.

For those wanting to know the contribution of air pollution to the total burden of mortality, in the Apheis cities particulate pollution contributed in a non-negligible manner to this burden as follows:

• All other things being equal, when only considering very short-term exposure, the proportion of all-causes mortality attributable to a reduction to 20 µg/m^3 in raw PM10 levels would be 0.9% of the total burden of mortality. This proportion would be greater, 1.8%, for a cumulative short-term exposure up to 40 days. Effects of long-term reduction in corrected PM10 levels would account for 7.2% of the burden of mortality.

• For long-term exposure to PM2.5 converted from corrected PM10, all other things being equal, the proportion of all-causes mortality attributable to a reduction to 20 µg/m^3 in converted PM2.5 levels would be 4% of the total burden of mortality.

Apheis also rose that from the public health perspective, the health impact of daily exposure to air pollution on the long run is much higher than the exposure to air pollution peaks (Figure 5).

<u>Interpretation</u>

In order to provide a conservative overall picture of the impact of urban air pollution on public health in Europe, like its predecessor Apheis 2, the Apheis 3 program used a limited number of air pollutants and health outcomes for its HIAs.

Apheis 3 also established a good basis for comparing methods and findings between cities, and explored important HIA methodological issues through sensitivity analyses to gain a better sense of the overall uncertainty of our estimates (WHO 2000, 2001, Le Tertre et al. 2005).

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[2] For HIAs of short-term exposure, we used raw PM_{10} and BS levels <u>measured directly</u> at monitoring stations

[3] For HIAs of long-term exposure, because the exposure-response functions used are taken from a publication that used gravimetric methods (Pope et al. 2002), for consistency we had to correct the automatic PM_{10} measurements used by most of the cities by a specific <u>correction factor</u> (local or, by default, the European factor of 1.3) in order to compensate for losses of volatile particulate matter.

[4] For most of the cities, $PM_{2.5}$ measurements were not available, and $PM_{2.5}$ levels had to be calculated from PM_{10} measurements. For this purpose a <u>conversion factor</u> (local or, by default, the European factor of 0.7) was used.

Below we discuss these methodological considerations as they apply to exposure assessment; health outcomes and baseline rates; and concentration-response functions.

Exposure assessment

Our HIA findings depend directly on the levels of particulate pollution measured. These levels vary widely as a function of the number and location of the monitoring sites, the analytical methods used, and the sites selected for our HIA.

In order to harmonise and compare the information relevant to exposure assessment by the 26 Apheis cities, the exposure measurements used in Apheis 3 were interpreted in accordance with the Apheis guidelines on exposure assessment prepared by the exposure assessment advisory group. In specific we verified the total number and type of monitoring stations and the number used for HIA purposes; the measurement methods; the use of a correction and/or conversion factor; and the quality assurance and control, and data quality.

Measurement intervals for air quality indicators

Because the C-R functions selected for HIAs of short-term exposure use the 24h average measurement interval, the Apheis guidelines recommended 24h averages for PM10, PM2.5 and BS, and the Apheis cities complied with the given recommendations for all monitoring stations. For HIAs of long-term exposure, the C-R functions selected used annual levels, so the Apheis cities did likewise.

Number of stations and site selection

Altogether 142 monitoring stations were selected for HIAs in accordance with the Apheis site-selection criteria. In a few cities, only one or two stations were used, but these were background stations and could reflect minimally the population exposure. In three cities, 28 stations were classified as directly traffic-related and should theoretically be excluded for HIA calculations. Despite this, the data from these stations was used for HIA because: 1) local experts considered the data from the stations was the most representative of the population's exposure in those cities; 2) C-R functions used for HIA of short-term exposure used these direct traffic-related stations, although it was not the case for studies selected for HIAs of long-term exposure.

Measurement methods

The Apheis centers reported the PM10/PM2.5/BS/TSP measurement methods in full, and used automatic PM10 measurement methods (the ß-ray absorption method and the tapered oscillating microbalance method [TEOM]). PM2.5 measurements were done only by TEOM. Reflectometry is the commonly used measurement method of BS. TSP was measured by ß-ray absorption method in one city and by gravimetric method in the second.

Local or, by default, European correction factors for PM10 were used for the purpose of long-term HIAs in order to compensate for losses of volatile particulate matter. In general, local conversion factors were slightly lower than the European factor of 1.3 recommended by the EC working group on Particulate Matter.

Beside this correction factor, conversion factors (local or European) were given for calculating PM10 from TSP measurements, as well as for PM2.5 data calculated from PM10 measurements. As a reminder, the default factor of 0.7 for PM2.5 was recommended by the Apheis Exposure Assessment working group. For Apheis cities that could compare both the annual mean levels of PM2.5 directly measured and PM2.5 converted from PM10 calculated using the European conversion factor (0.7), in most of the cities the annual mean level of PM2.5 measured directly was a little lower than the annual mean level of PM2.5 converted from PM10 calculated using the European conversion factor.

Overall, the assessment of exposure data in Apheis 3 was sufficiently reliable for our HIA purposes.

Health outcomes

The Apheis centers provided a full description of the health indicators used for Apheis 3, the type of sources, the coverage, the existence of a quality-control program, the type of coding used, and the completeness of the data.

Mortality data

The information sources for mortality data were the national, regional or local mortality registries for all the cities. In Apheis 3, cause-specific mortality was included beside all-causes mortality to enrich the mortality picture. But all-causes mortality remains our first choice, because it is more robust, not subject to misclassification and easier to obtain.

Because most of the cities applied a quality-control program and because of the low percentage of missing data for all-causes mortality, we consider that erroneous entries in the selection of cause of death did not affect the comparability of the data between cities.

Hospital admissions data

To estimate the acute effects of short-term exposure to air pollution on hospital admissions, in each city we selected hospital admissions for residents with discharge diagnoses of respiratory diseases (ICD9: 460-519; ICD10: J00-J99) and cardiac diseases (ICD9: 390-429; ICD10: I00-I52). Whenever possible, only emergency admissions were selected as more specifically related to air pollution, and discharge diagnoses were used in all cases because they are more reliable.

All the cities obtained the data from registries. The completeness of the registries on hospital admissions was quite high, 95% or more in 18 of the 22 cities.

All the registries run a quality-control program, and completeness in the diagnosis for the cause of admission was high, with a percentage of missing data of 1% or lower for 19 of the 22 registries.

The main problem for comparability remains the difference in the availability of information in the registries, because some cities used emergency admissions, while others that lacked this information used general admissions.

Methodologically speaking, statistical analyses of the Aphea 2 cities showed no significant heterogeneity in the estimated relative risk (RR) of hospital admissions between cities that reported general hospital admissions and those that reported emergency hospital admissions only (Atkinson 2001, Le Tertre 2002). This might seem initially surprising but in fact is very reasonable. General admissions include both planned and emergency admissions, and when controlling for season we also control for general trends for both admissions, and finally what is left is emergency admissions and some background noise.

Nevertheless, this raises an issue for HIA if general admissions are used rather than emergency ones and the same RR is applied. We should investigate the possibility of using a correction factor from emergency admissions and apply it to general admissions. There is also a need to examine this and other approaches on how best to handle the difficult situation of HIA when baseline data is unknown, missing or collected in different ways.

The analysis of health data quality and availability concluded that, for local use in each city, the selected data was reliable. When comparing findings between cities, the data was fully comparable for the selected categories of mortality. Nevertheless, even if most of the cities have hospital data from registries that use a quality-control program, such comparability was limited, however, for the incidence of hospital admissions. The incidence rates from emergency and total admissions (Figure 6) appear not to be fully comparable. Consequently, we presented data for hospital admissions and the resulting HIAs in the city-by-city reports only. In an upcoming new phase of the program Apheis will investigate the influence of health-care and health-monitoring systems on morbidity data for HIAs .

Concentration-response functions

Most HIAs, including ours, use overall estimates from multi-centre studies. But in some cases, people prefer to use city-specific estimates when they conduct an HIA in a particular city where an epidemiological study has been done that provides local E-R functions. This issue of using alternatively city-specific estimates has been discussed in Apheis and the statistical advisory group conducted a sensitivity analysis using different effect estimates (Le Tertre et al. 2005).

Sensitivity analysis using different types of estimates

The Apheis statistical advisory group conducted a sensitivity analysis in some cities to address the issue just mentioned and used different effect estimates (observed city-specific, shrunken city-specific, pooled, mixture of shrunken city-specific and adjusted for effect modifiers) to calculate the number of "premature" deaths in each city. The study concluded that, although the sum for 21 European cities of the deaths attributable to PM10 is not strongly influenced by the method used to estimate Relative Risks (RRs), this is not true at the city level.

Applied to a single city, the different estimates tested present benefits and limits, and based on these limitations the authors recommended the use of the shrunken estimate in cities for which this option is available. Use of this shrunken estimate enables deriving the overall estimate at the local level by combining information from the city-specific estimate and the overall one, and can be considered as a weighted mean between these two estimates. Its use also reduces the variability of the local estimate by incorporating information from other cities. However a key disadvantage of such an estimate is that it can only be applied in cities that are part of the initial multi-center analysis.

Figure 7 shows the estimated density for each of the shrunken estimators (i.e., in each city). Superimposed is the estimated distribution of the pooled estimate (i.e., Overall), based on the random effects model, and the estimated mixture distribution of the Empirical Bayes estimates across all the cities. Substantial departures from the population mean (overall) estimate can be seen in several cities. The underlying distribution of the Empirical Bayes estimates displays the same mean as the pooled estimate, but it is more flat, reflecting the heterogeneity between cities. Consequently the corresponding 95% credible interval for the Relative Risk for total mortality associated with a 10 $\mu g/m^3$ increase in PM10 (0.994, 1.014) is larger than the one derived from the pooled estimate (1.002 to 1.006).

The statistical advisory group recommends the use of an estimated mixture distribution of the shrunken estimates that will give the same central estimate as the overall pooled one but with a larger confidence interval, avoiding excessive certainty suggested by naïve approaches to risk assessment. The use of this type of estimate will be proposed at the city level in the next HIAs.

When building our own C-R functions on respiratory admissions all ages, we used the Aphea 2 methodology (Katsouyanni et al 2001) based on time series analysis taking into account the problems with GAM raised by NMMAPS (Dominicci et al. 2002) and investigating the sensitivities of the estimated pollution effects by using alternative smoothing techniques, parametric and non-parametric, and by using a range of smoothing parameters. Since we use aggregated data in Apheis, we prefer using a time-series approach instead of case-crossover analysis. In addition, only a time-series approach can take overdispersion into account (Lu and Zeger 2007).

Apheis will continue to investigate important methodological issues and uncertainties surrounding HIA findings in its new EC co-funded project, Aphekom.

Achievements

Among others the Apheis program has:

• Created an active public-health and environmental network that facilitates the flow of information between environmental and health professionals, and developed expertise across Europe

• Guided and optimized the measurement of air pollutants by local air-quality-monitoring networks so these networks meet the needs of public-health monitoring
• Contributed to the training of environmental-health professionals
• Provided information to evaluate the effectiveness of different scenarios for reducing air-pollution levels on local, national and European levels
• Gained recognition from local and national authorities as able to provide sound scientific advice on health risks related to air pollution
• Attracted interest from cities not involved in the Apheis program to join the Apheis network

Impact of the Apheis project

Implications for EU policy making

To contribute to the discussions between the European Council and the Parliament on new limit values for PM2.5, the Apheis project estimated the potential benefits in terms of deaths that could be postponed in 26 European cities by reducing PM2.5 annual levels to 25, 20, 15 and 10 $\mu g/m^3$ respectively. In specific, reducing annual mean levels of PM2.5 to 15 $\mu g/m^3$ could postpone three times more premature deaths in the Apheis cities than a reduction to 25 $\mu g/m^3$ (13,200 vs. 4,400 deaths) (Figures 8). This number could grow by up to five times if PM2.5 levels were reduced to 10 $\mu g/m^3$ (22,200 vs. 4,400 deaths). Apheis also made a sensitivity analysis to check the changes in HIA estimates using other C-R Functions or other correction factors for the ratio of PM2.5/PM10, and the main conclusions here remained the same (Ballester et al. 2008).

Impact on the centers' work and on policy making

<u>Impact on the centers' work</u>

Centers learned the philosophy, methods and tools of the HIA approach. Apheis improved scoping, appraisal and reporting of HIA stages.

The Apheis project provided an opportunity to harmonize existing local and national approaches to HIA. Apheis enabled many cities to conduct enlarged local, regional and national HIAs. Apheis "stimulated us to go further with both national and local HIAs" and obtain funding for this purpose (Stockholm and Gothenburg, Sweden; Andalucia, Spain).

Apheis fostered dialog between environment and health professionals locally. Apheis also led to the exchange of know-how in different fields at the EU level. And gave centers the opportunity to meet with international experts and create lasting relationships with them. "A significant impact due to the international dimensions of the project" (Bucharest, Romania).

Involvement in the Apheis project made local findings more credible. Apheis provided the centers with "a stimulus from the outside" that facilitated local work on air pollution and health. "Involvement in the Apheis project increased the prestige of our team" (Madrid, Spain).

Centers valued being able to compare findings with those of other cities. "Use of international benchmarking was a good starting point for a science-based discussion of the overall and local results" (Hamburg, Germany).

Apheis provided an opportunity to apply HIA to other fields, e.g., domestic heating (Vienna, Austria), and opened doors for related HIA projects (Stockholm and Gothenburg, Sweden).

Apheis methodology was applied in the framework of Enhis 2 project to develop an online tool for the HIA of urban air pollution using European data bases and/or local data (www.hiair.eu).

Impact on policy making

Apheis findings contributed to local, regional and national environmental-health action plans. Local centers were asked to speak to local and national authorities. With Apheis "We can show people and policy makers a clear result about impact of air pollution on health." "Apheis findings are very helpful in the current discussion on reducing air pollution in big cities" (Ljubljana, Slovenia). "Apheis findings, beside other results on the impact of air pollution on health, led the Spanish Government to approve the new Law on Air Quality" (Valencia, Spain).

Apheis raised awareness through the mass media and NGOs. HIA findings were easier to communicate than other findings (Stockholm and Gothenburg, Sweden). "The results of Apheis were always attractive for journalists, much more than telling them about RRs or ORs. So HIA provides a very useful tool for informing the public." (Athens, Greece). "The picture with air pollution influence on life expectancy had a huge impact in the Netherlands. It was very helpful to translate scientific information into pictures." (Rotterdam, Netherlands). "The assessment of long-term impact of air pollution, especially years of life lost, was extremely useful for us" in terms of communication. (Budapest, Hungary).

"Apheis creates a good framework in which results can be properly assessed and compared with others from similar and different places." (Bilbao, Spain). "We used the Apheis information for benchmarking, which is very important for civil servants and politicians who want to know if they have unique problems or if problems are similar in other cities." (Rotterdam, Netherlands).

Problems remain

While Apheis increased awareness among the general public of the impact of air pollution on health, there has generally been little change in its behavior. In some countries, Apheis findings had little impact because of higher national priorities (Israel) and because other sources of information on the effects of air pollution on health were available (Rome, London).

Centers were concerned by the lack of EU willingness to fund a European system for monitoring the effects of air pollution on health on a continuous basis.

Conclusions for the EHTP and other projects

To compare methods and findings between cities:

• Build a collaborative network from the bottom up to stimulate cooperation and facilitate decision making on the local, national and higher regional levels
• Use standardized protocols and tools for data collection (short and long term) and HIA analysis
• Keep it simple to ensure feasibility and compliance in the long term
• Involve local committees from the outset
• Foster ongoing cross-fertilization between multiple disciplines and regions to create skilled, local teams; enrich know-how and the quality of its findings; and explore HIA methodological issues

Remember, however, that public-health findings continue to have a limited impact on policy making, since decision makers are influenced by other factors they consider to be more important when setting policy. Hence, we might consider whether we should put more emphasis in our training sessions on how to "sell" public-health findings to government policy makers and influencers. So work more with communication-strategy professionals.

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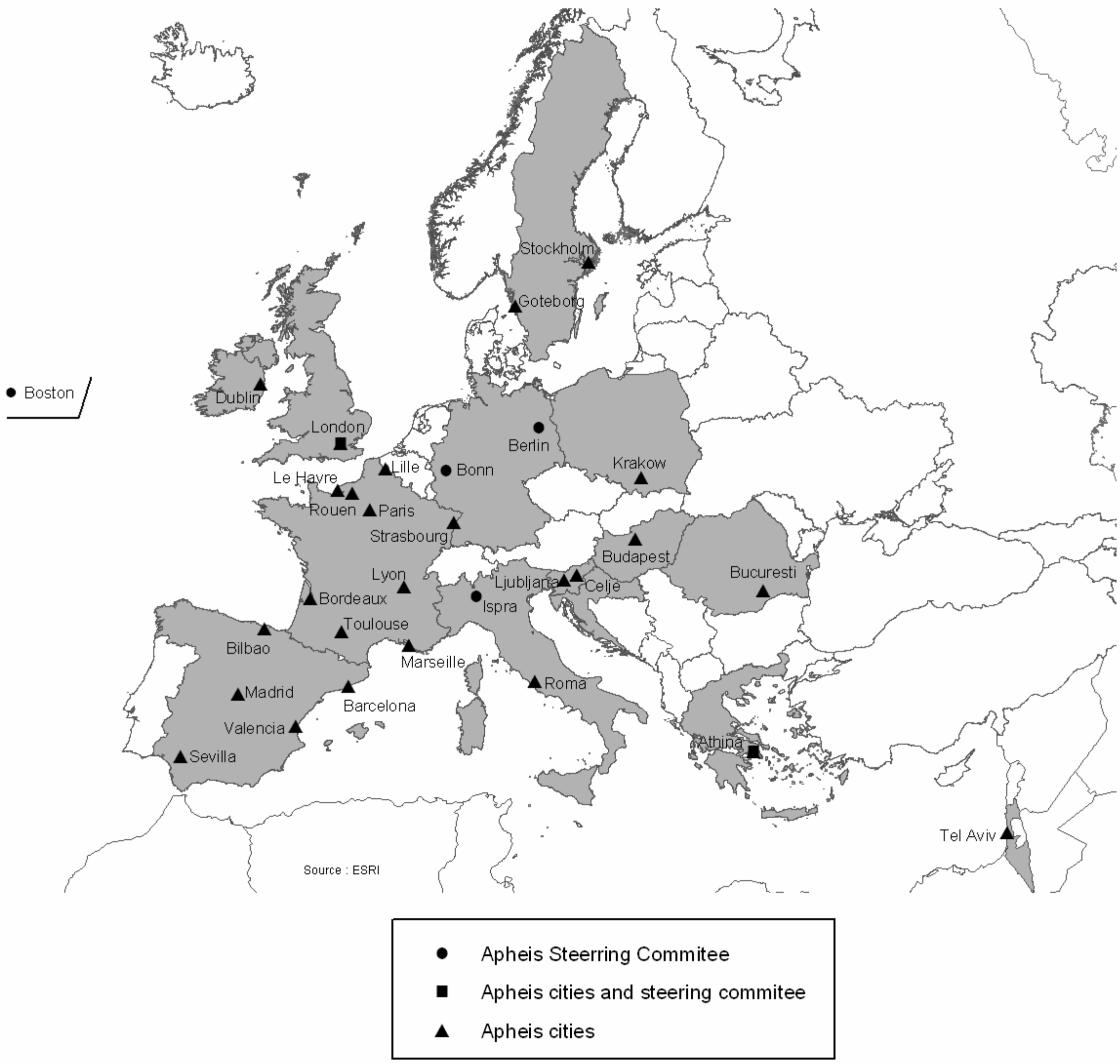
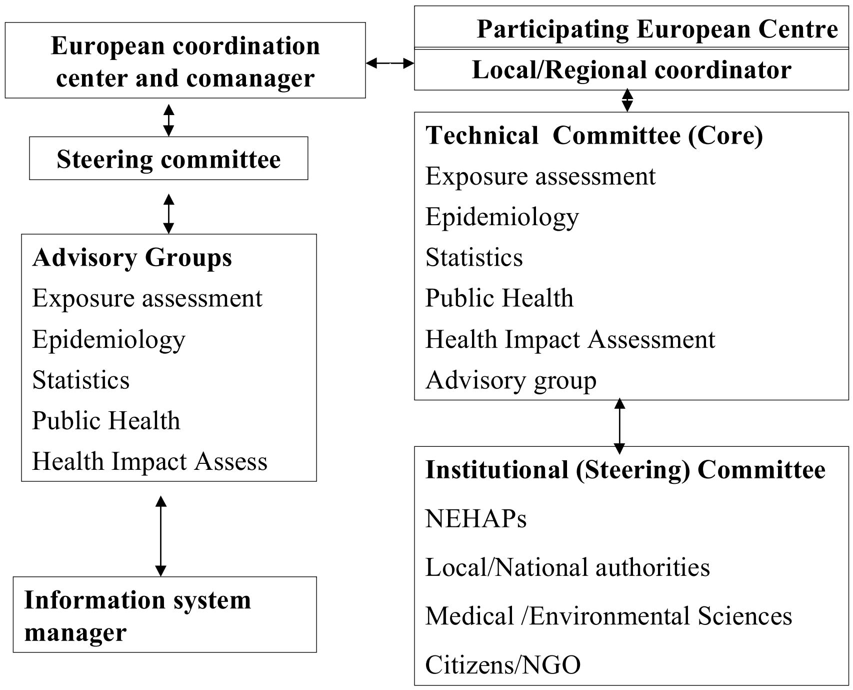
ANNEX B

Figure 1. The Apheis network



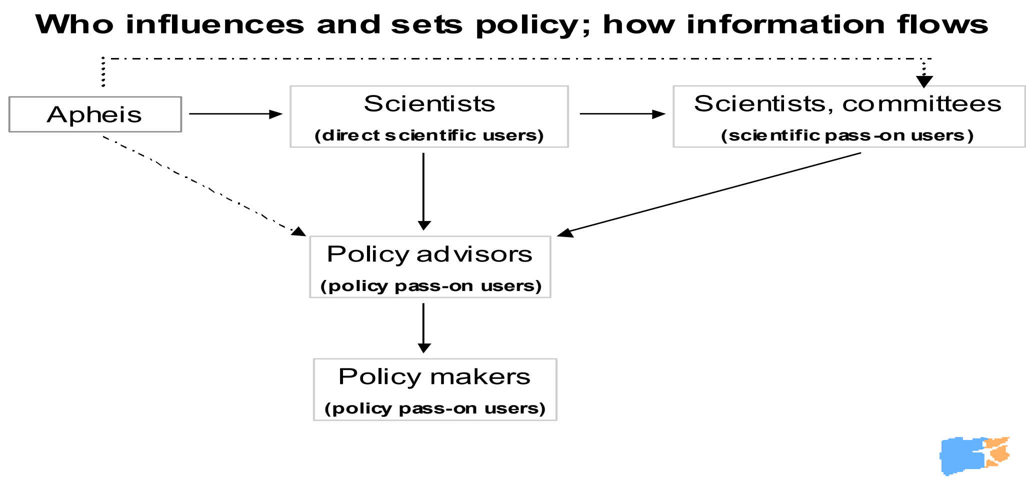
ANNEX B

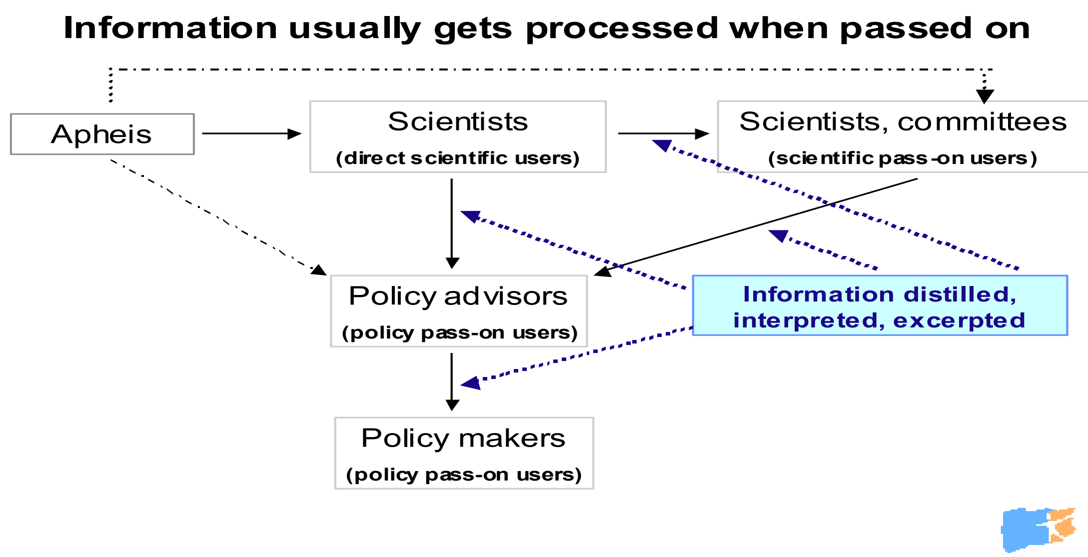
Figure 2. Apheis general organizational model and functions

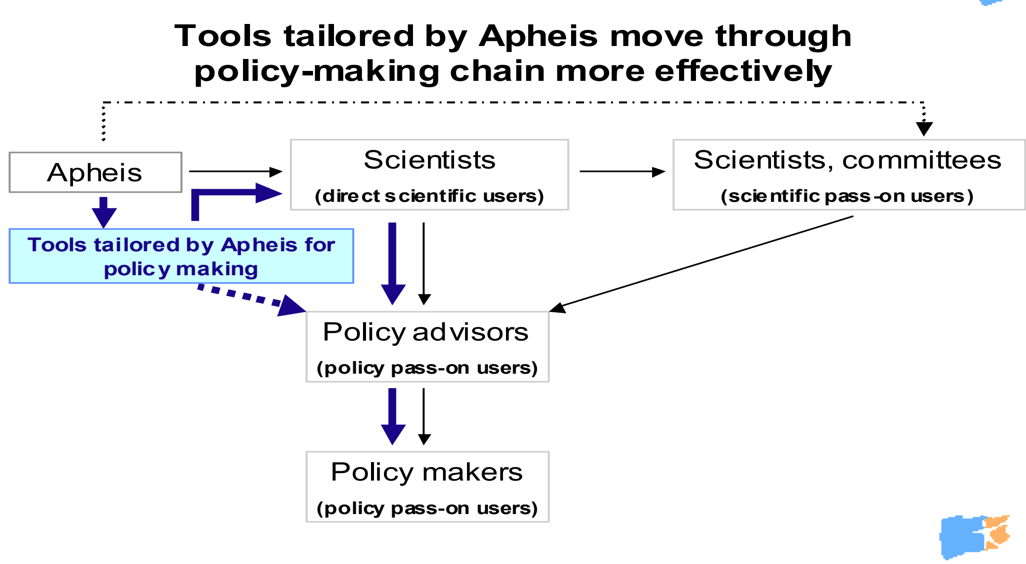


ANNEX B

Figure 3. Apheis Communication Strategy







ANNEX B

Table 1. Summary of data components used for health impact assessment on short-term exposure in Apheis 3.

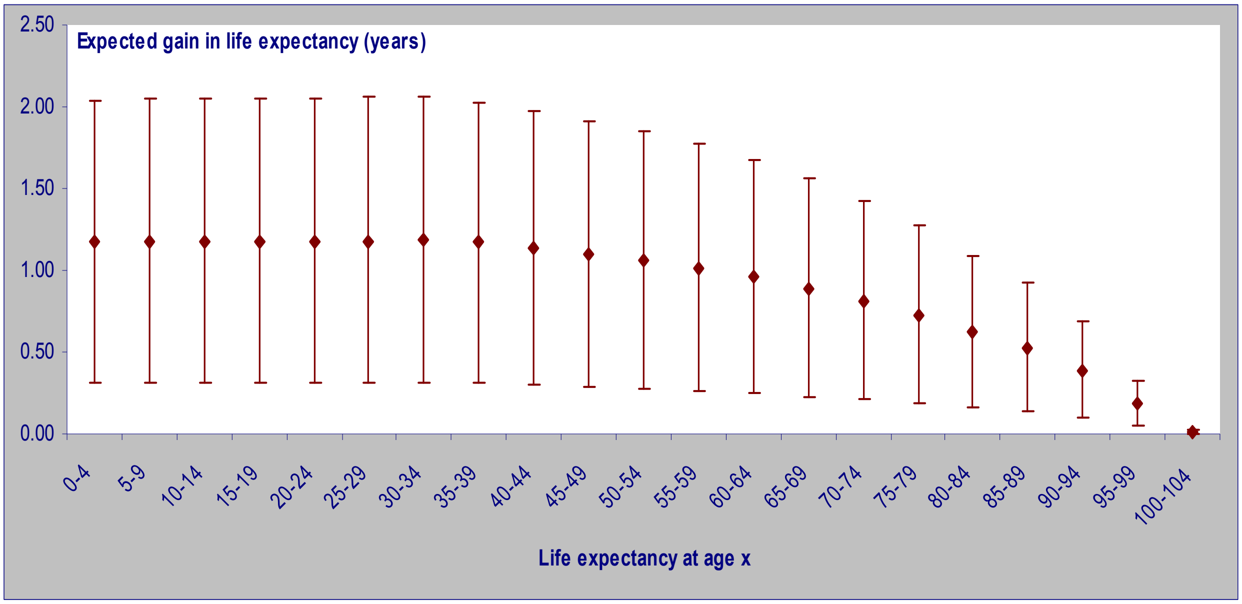
Summary SHORT-TERM HIA							
	Health indicator	ICD		Tool	RR (95% IC) For 10 µg/m^3 increase	Scenarios	References
Attributable cases		**ICD9**	**ICD10**			**Daily mean**	
ST HIA for all Apheis cities							
Black smoke	All ages, all causes mortality (excluding external causes) All ages, cardiovascular mortality All ages, respiratory mortality All ages, cardiac hospital admissions All ages, respiratory hospital admissions	< 800 390-459 460-519 390-429 460-519	A00-R99 I00-I99 J00-J99 I00-I52 J00-J99	PSAS-9 Excel spreadsheet	1.006 (1.004 - 1.009) 1.004 (1.002 - 1.007) 1.006 (0.998 - 1.015) 1.011 (1.004 - 1.019) 1.0030 (0.9985 -1.0075)	Reduction to 50 µg/m^3 Reduction to 20 µg/m^3 Reduction by 5 µg/m^3	WHO, 2004 WHO, 2004 WHO, 2004 APHEIS 3, 2004 APHEIS 3, 2004
PM_{10} very short-term	All ages, all causes mortality (excluding external causes) All ages, cardiovascular mortality All ages, respiratory mortality All ages, cardiac hospital admissions All ages, respiratory hospital admissions	< 800 390-459 460-519 390-429 460-519	A00-R99 I00-I99 J00-J99 I00-I52 J00-J99	PSAS-9 Excel spreadsheet	1.006 (1.004 - 1.008) 1.009 (1.005 - 1.013) 1.013 (1.005 - 1.021) 1.006 (1.003 - 1.009) 1.0114 (1.0062 - 1.0167)	Reduction to 50 µg/m^3 Reduction to 20 µg/m^3 Reduction by 5 µg/m^3	WHO, 2004 WHO, 2004 WHO, 2004 APHEIS 3, 2004 APHEIS 3, 2004
PM_{10} cumulative short-term (40 days)	All ages, all causes mortality (excluding external causes) All ages, cardiovascular mortality All ages, respiratory mortality	< 800 390-459 460-519	A00-R99 I00-I99 J00-J99	PSAS-9 Excel spreadsheet	1.01227 (1.0081 - 1.0164) 1.01969 (1.0139 - 1.0255) 1.04206 (1.0109 - 1.0742)	Reduction to 50 µg/m^3 Reduction to 20 µg/m^3 Reduction by 5 µg/m^3	A. Zanobetti et al, 2002 A. Zanobetti et al, 2003 A. Zanobetti et al, 2003
Complementary ST HIA for some Apheis cities							
PM_{10} with shrunken estimates	All ages, all causes mortality (excluding external causes)	< 800	A00-R99	PSAS-9 Excel spreadsheet	RRs calculated from betas & se of Apheis shrunken estimates for each city	Reduction to 50 µg/m^3 Reduction to 20 µg/m^3 Reduction by 5 µg/m^3	Apheis 3, 2004

Table 2. Summary of data components used for health impact assessment on long-term exposure in Apheis 3.

Summary LONG-TERM HIA							
	Health indicator	**ICD 9**	**ICD10**	**Tool**	**RR (95% IC) For 10 µg/m^3 increase**	**Scenarios**	**References**
LT HIA for all-cities report							
Attributable cases						**Annual mean**	
PM_{10}	All causes mortality (excluding external causes)	< 800	A00-R99	PSAS-9 Excel spreadsheet	Trilateral & Apheis 2 1.043 (1.026 -1.061)	Reduction to 40 µg/m^3 Reduction to 20 µg/m^3 Reduction by 5 µg/m^3	Kunzli et al. 2000
$PM_{2.5}$	All causes mortality Cardiopulmonary mortality Lung cancer	0-999 401-440 and 460-519 162	A00-Y98 I10-I70 and J00-J99 C33-C34	PSAS-9 Excel spreadsheet	Average Pope, 2002 1.06 (1.02 - 1.11) 1.09 (1.03 - 1.16) 1.14 (1.04 - 1.23)	Reduction to 20 µg/m^3 Reduction to 15 µg/m^3 Reduction by 3.5 µg/m^3	C.A. III Pope, 2002 C.A. III Pope, 2002 C.A. III Pope, 2002
Gain in life expectancy						**Annual mean**	
$PM_{2.5}$	Age > 30 only All causes mortality Cardiopulmonary mortality Lung cancer	0-999 401-440 and 460-519 162	A00-Y98 I10-I70 and J00-J99 C33-C34	AirQ	Average Pope, 2002 1.06 (1.02 - 1.11) 1.09 (1.03 - 1.16) 1.14 (1.04 - 1.23)	Reduction to 20 µg/m^3 Reduction to 15 µg/m^3 Reduction by 3.5 µg/m^3	C.A. III Pope, 2002 C.A. III Pope, 2002 C.A. III Pope, 2002

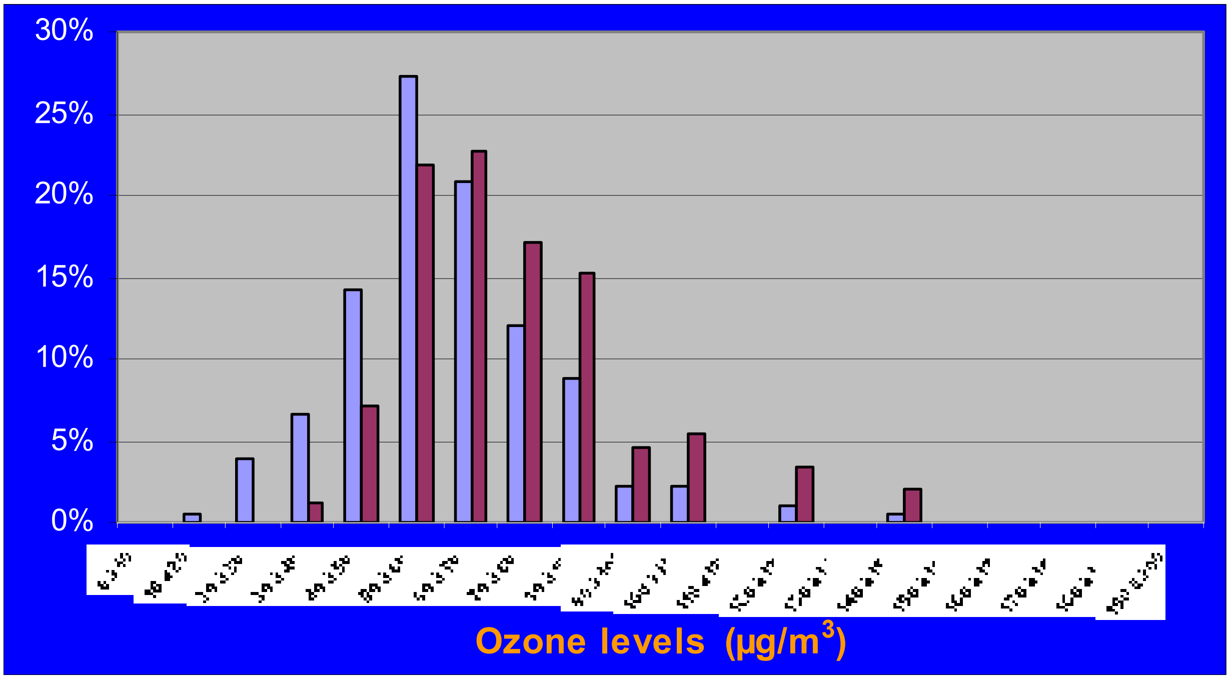
ANNEX B

Figure 4. Expected gain in life expectancy if $PM_{2.5}$ annual mean levels would not exceed 15 µg/m^3 in Seville.



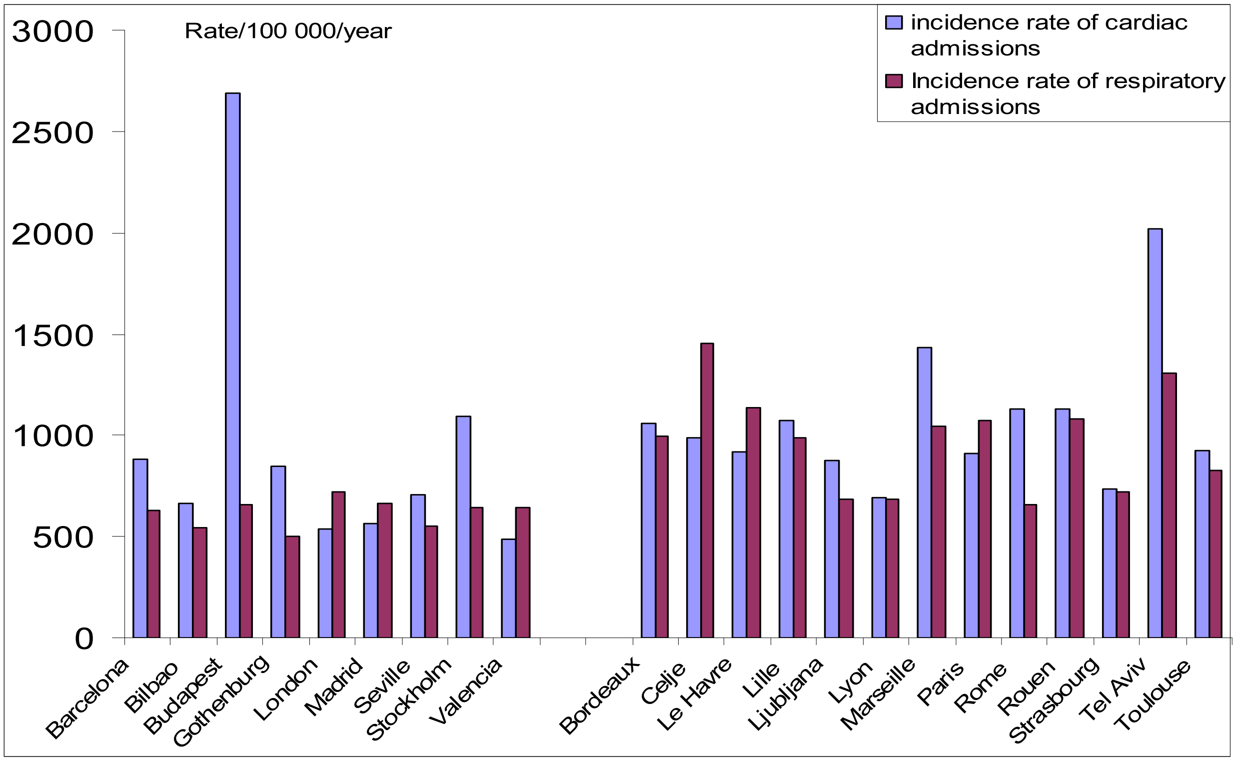
ANNEX B

Figure 5. Distribution of ozone daily mean levels and increase in daily mortality (summer) Caen, France



ANNEX B

Figure 6. Incidence rates for hospital admissions in 22 cities (9 with emergency admissions, 13 with general admissions)



I--- -----------------------------------I I-- I
Cities with emergency admissions Cities with general admissions

Figure 7. Probability densities of PM_{10} shrunken coefficients for mortality in each of the 21 cities and resulting estimated mixture distribution from all cities. Shown is also the probability density of the pooled over all cities (using random effects model) coefficient.

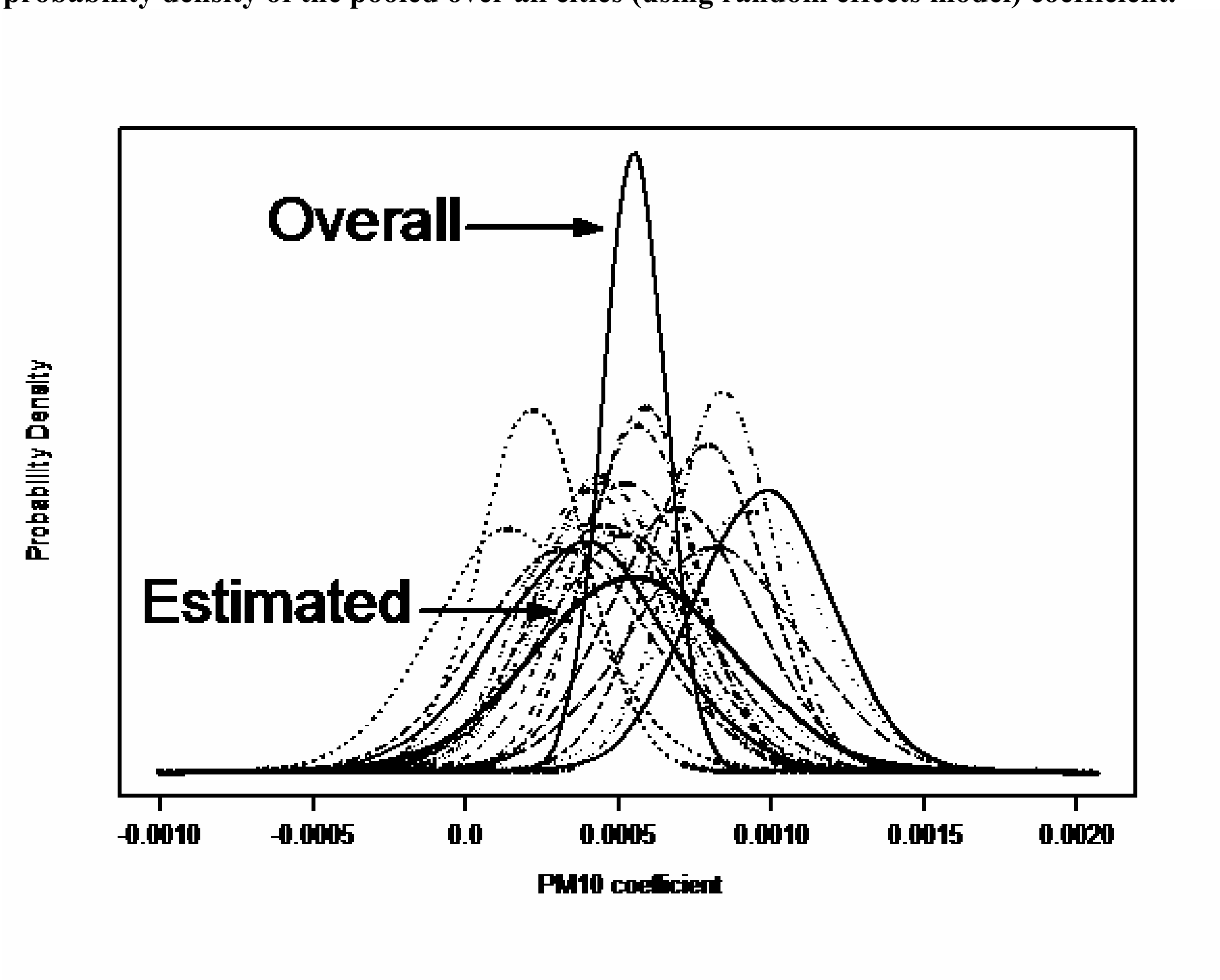
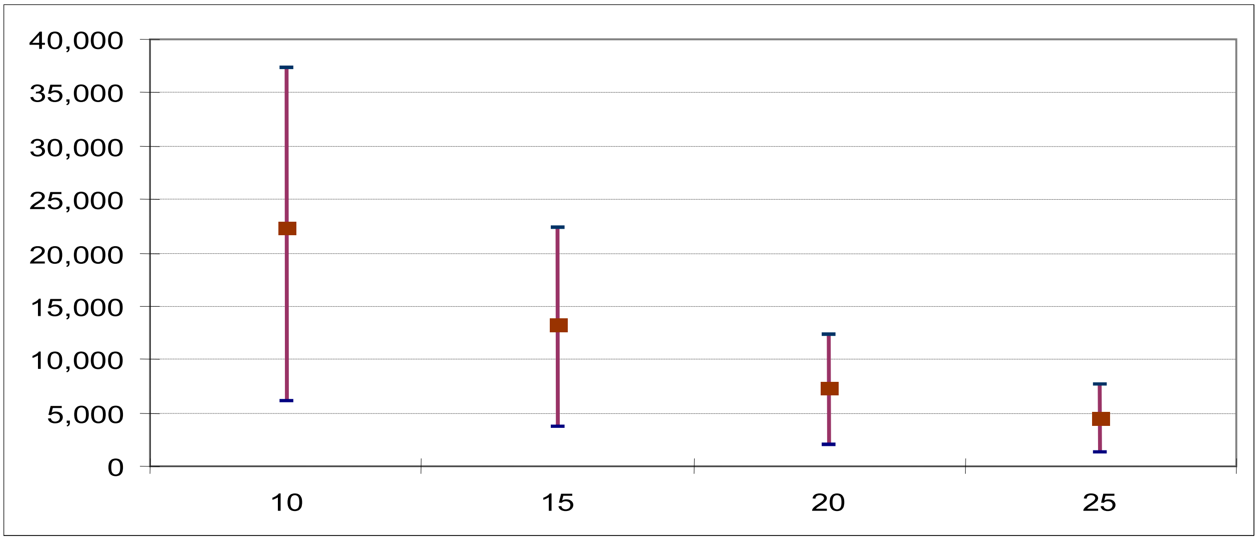


Figure 8. Potential postponements in total annual deaths (central estimate and 95% CI) among people age 30 years and over in the 26 Apheis cities for different decreases in annual PM2.5 levels.



Scenarios for reduction of annual $PM_{2.5}$ levels (µg/m^3)

ANNEX B8.

Shin HH, Stieb DM, Jessiman B, Goldberg MS, Brion O, Brook J, Ramsay T, Burnett RT. Measuring Public Health Accountability of Air Quality Management.

Measuring Public Health Accountability of Air Quality Management

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ABSTRACT

Accountability of air quality management is often measured in by tracking ambient pollution concentrations over time. These changes in ambient air quality are rarely linked to changes in public health, a major driver for such programs. We propose a method to assess the accountability of air quality management programs with respect to improvements in public health by estimating national temporal trends in attributable health risk. The Air Health Indicator is a tri-variate function based on the annual pollution concentrations, annual estimates of health risk obtained by time series statistical methods, and the percent attributable risk (the product of concentration and risk). Random effects models are used to obtain a distribution of risk over both space and time. The model is illustrated by examining the association between daily non-accidental deaths in 24 of Canada's largest cities and daily concentrations of ozone and nitrogen dioxide over the 17 year period 1984-2000.

1. INTRODUCTION

The Canadian Government has initiated a program to monitor the quality of the environment as one predictor of social and economic well-being. One way to assess environmental quality is to use indicators that convey complex information in a simple form. Canadian Environmental Sustainability Indicators (CESI) provides an indication of the health of our environment in much the same way as the gross domestic product and other signals provide a sense of the health of the economy. CESI has three components: air quality, fresh water quality, and greenhouse gas emissions. Spatial-temporal trends in these components are reported annually (CESI, 2006). Social, economic, and climatic factors are examined in order to understand the causes of observed spatial and temporal variations. Each successive reporting year is based on an additional year of monitoring data.

The air quality component of the Indicator measures annual average concentrations of ozone and fine particulate matter averaged over all monitors within a community and then population-weighted averaged over all communities. As of the 2007 report, annual averages for ozone are reported from 1990 to 2005 with annual averages of fine particulate matter reported for the 2000 to 2005 time period. A non-parametric statistical test for monotonic trend in the annual averages is presented (Sen, 1968)). Annual averages are also reported by region of the country.

When more stringent air quality standards are set and subsequently meet, it is implicitly assumed there will be some improvement in public health (USEPA, 1997; DeCivita et al., 1999). Such improvements in public health are rarely verified other than in a few isolated cases (Clancy et al., 2002; Freidman et al., 2001; Hedly et al., 2002; Pope, 1989). If the relationship between concentrations of ambient air pollution and various health outcomes, such as mortality and hospital admissions, remain constant over time then there would be little need to verify if improvements in air quality do in fact translate into improvements in public health. However, the relationship between outdoor air pollution and health can change over time and space for several reasons. First, the nature and extent of the at-risk population may change over time (e.g., through an aging population, changes in prevalence of health conditions) and may also vary across the country due to spatial-temporal variation in population demographics and disease status. Second, some measured ambient air pollutants may act as markers for the truly toxic but unmeasured atmospheric constituents. For example, particulate mass, a pollutant often linked to health, is composed of hundreds of chemical compounds, whose concentrations can vary dramatically over both space and time. Strategies to reduce the particulate phase of the mixture may reduce mass but not proportionately reduce the toxicity of the atmospheric mixture. Third, the shape of the concentration-response relationship may not be linear and thus changes in the distribution of exposures over time may lead to changes in the estimate of risk based on the commonly employed linear association between concentration and response. Finally, the relationship between measurements of pollution from fixed-site outdoor monitors and the exposure metric of most interest (i.e., population-average personal exposure) may also vary over space and time arising from changes in monitor location over decades, within and between community changes in population density, housing stock, air conditioning use, and time activity patterns. It is therefore of interest to be able to track changes in the relationship between outdoor air pollution in urban environments and health in both space and in time.

Several studies have used spatial variation in risk (between cities) to identify factors that modify risk, such as percent of homes in a city with air conditioning. We can also use time as a means of generating additional variation in risk estimates in order to understand what factors influence the relationship between exposure and response.

There have been several studies linking daily variations in urban air pollution and daily variations in the number of deaths within a city throughout the world (Stieb et al, 2002). Most countries maintain mortality records, thus providing a resource to routinely track an important aspect of adverse health risks associated with air pollution. Computerized records of admissions to hospital for all ages are also available and have been linked to air quality in Canada (Burnett et al., 1994; 1997; 1999; 2001; Lin et al., 2002). Hospital admissions are a marker for an adverse health event. One is interested in reducing the number of adverse events, not simply admissions to hospital. The fact of being admitted to a hospital can be influenced by a number of factors including the role the hospital plays in health care delivery. This role may be changing over time in Canada. For example, hospital admissions for asthma among those 0-24 years of age have declined by approximately one half between 1987 and 2004. This has been attributed to both improved medical care and reduced availability of hospital beds (PHAC 2007). Declines in age-adjusted hospital admission rates for cardiovascular disease have also been reported (Johansen et al. 2005). This issue is not as much a concern for emergency room visits because everyone who visits the emergency room is examined and a record is created for that visit. Potentially changing patterns of how Canadians obtain their health care, such as increases in walk-in clinics, can also influence emergency room visits frequencies. Unfortunately, Canada does not have a centralized computerized emergency room record system so universal coverage of this outcome is not currently available.

Our approach to estimating risk over space and time is illustrated by the case of the association between two pollutants shown to be related to mortality in Canadian cities (Burnett et al., 2004), nitrogen dioxide and ground level ozone, and non-accidental mortality in 24 of Canada's largest cities over the 17 year period from 1984 to 2000.

2. SPATIAL-TEMPORAL MODEL FOR RISK OF AIR POLLUTION

The number of daily non-accidental deaths was selected as the response variable reflecting the adverse short-term health effects from air pollution. To measure the association between short-term exposure to ambient air pollution and death, we consider a time series of the counts of daily deaths on day t within community i, $Y_i(t)$, and the corresponding concentration of an ambient air pollutant, $x_i(t)$. A Poisson regression model applied to the counts can be simplified as

$$\log(E[Y_i(t)]) = \beta_i(t)x_i(t) + \text{confounder}_i(t).$$

The unknown parameter $\beta_i(t)$ represents the unit log-relative risk at time t for community i. The focus of our analysis is to model how risk varies over time and between communities. Since we are most interested in changes in risk over time periods on the order of years, we will assume the risk is constant within each calendar year. Temporal structure of risk can be therefore simplified as $\beta_i(t) = \beta_{ij}$ for all t in the j^{th} calendar year.

We consider three factors as potential confounding variables: time; temperature; and indicators for days of the week (DOW). Time is included to control both temporal and seasonal variations, daily temperature controls for the short term effect of weather on daily mortality, and day of the week accounts for mortality that varies by day of the week. Daily counts of mortality are assumed to depend on time and temperature in a non-linear fashion and on air pollution in a linear manner.

To be consistent with the CESI reporting of ambient air pollution trends, we based our temporal-spatial risk estimator on the data for each city and year. The estimation procedure has two stages. City and year specific estimates $\hat{\beta}_{ij}$ are obtained from an overdispersed Poisson time series model in addition to estimates of their error variances $\hat{v}_{ij}$ (see Ramsay et al., 2003 for details of this procedure). We note that other estimation approaches can be considered in the first stage, such as case-crossover (Lin et al,. 2002) or generalized linear mixed models (Szyszkowicz, 2006).

In the second stage we consider a random effects model of the form:

$$\hat{\beta}_{ij} = \mu_\beta(j) + \delta_{ij} + e_{ij},$$

where δ_{ij} is an independent random variable with mean 0 and variance $\sigma^2_\beta(j)$. This is a random effect model with the parameters fluctuating randomly around their mean $\mu_\beta(j)$. The e_{ij} are independent random variables with zero expectation and variance $\hat{v}_{ij}$ which is assumed known. The estimates $\hat{\beta}_{ij}$ are assumed to be normally distributed with a common mean, $\mu_\beta(j)$, and the variance modelled by the sum of two variances: the within community estimation variance, v_{ij}, and between community variance indicating the heterogeneity of the true risks among cities, $\sigma^2_\beta(j)$. Bayesian methods are used to obtain estimates of the distribution of risk among the communities annually, with expectation $\hat{\mu}_\beta(j)$ and variance $\hat{\sigma}^2_\beta(j)$ (Dominici et al., 2000). An estimate of the city-specific risk, $\tilde{\beta}_{ij}$ say, under the random effects model is also obtained. Since this estimate is always closer to $\hat{\mu}_\beta(j)$ than $\hat{\beta}_{ij}$, it is termed a "shrinkage" estimator. If $\hat{\sigma}^2_\beta(j) = 0$, then the "best" estimate of risk for any community is the common risk estimate. The larger the estimate of heterogeneity in risk ($\hat{\sigma}^2_\beta(j)$) compared to the within community error estimate ($\hat{v}_{ij}$), the closer shrinkage estimator $\tilde{\beta}_{ij}$ will be to the estimator of risk based soley on information from that city $\hat{\beta}_{ij}$. Although the shrinkage estimators are biased, they have smaller variances than $\hat{\beta}_{ij}$, thus providing more stable estimates. We are thus borrowing strength from all the communities to estimate risk for each specific location. This is particularly useful when examining smaller communities which inherently have large uncertainties with respect to their estimates of risk.

The estimate of heterogeneity in risk among cities is highly unstable over time (Shin et al., 2008). While the pooled risk estimates are relatively insensitive to this instability, the city-specific shrinkage estimators are not. We therefore use a common value of $\hat{\sigma}^2_\beta$ for determining both the pooled annual risk and the city-specific annual shrunk risks. This common value is defined as the median of the annual estimates of $\hat{\sigma}^2_\beta$ over the entire time period of observation. The same number of observations (ie. 365 days) are used to estimate both v_{ij} and σ^2_β.

The outputs from our model are then the pooled risk for each year and the annual city-specific shrunk estimates. The Air Health Indicator (AHI) is a tri-variate temporal function of national trend in ambient concentration, national trend in risk, and national trend in percent attributable risk (product of concentration and risk times 100).

3. ILLUSTRIATIVE EXAMPLE

Daily variations in non-accidental mortality in Canadian cities have been shown to be related to daily variations in both concentrations of ozone and nitrogen dioxide (Burnett et al., 2004). We illustrate our spatial-temporal model of risk using these pollutants. We consider the daily 8-hour running maximum as the summary measure of population average exposure for ozone since it is the metric employed for the Canada-Wide Ozone Standard (CCME, 2000). The daily average concentration is used for NO_2. We selected communities with a reasonably long time series of both pollutants, resulting in 24 Canadian cities having information from 1984 to 2000, the last year of nationally available mortality data. The cities span the geographic breadth of the country. The time series model comprises a natural spline term in the model for time with 9 *df*/year, two natural spline terms for daily average temperature with 3 *df* recorded on the day of and the day prior to death, indicator functions for the day of the week, and a linear term for the two day average of pollution concentrations.

The tri-variate components for the Air Health Indicator are presented in Figure 1 for ozone. There is some evidence that ozone concentrations have increased over the time period ($p=0.0435$) from 1984 to 2000 with a slope of 0.174 ppb/year and 95% confidence interval of (0.008, 0.346). This corresponds to a 10.8 % increase in concentrations over the observation period. However, there is little evidence ($p=0.4338$) that risk changes over time with a median slope of -1.96×10^{-5} log-mortality rate/ppb per year (-7.57, 2.82) corresponding to a 38.2 % decrease in risk over time. There is also little evidence ($p=0.5367$) that the percent attributable risk changes over time with a median slope of -0.033 %/ppb per year (-0.194, 0.114). This change in attributable risk corresponds to a 26.1 % decrease over the observation period.

The equivalent information is presented in Figure 2 for nitrogen dioxide (three left-hand panels). Nitrogen dioxide concentrations have clearly declined over time ($p<0.0001$) with a median slope of -0.275 ppb/year (-0.382, -0.236) corresponding to a 20.1% decline in concentrations over the entire time period. However, there is some evidence to suggest ($p=0.1275$) that risk has increased over time with a median slope of 4.180×10^{-5} log-mortality rate/ppb per year (-2.033, 10.207), which corresponds to a 122.3 % increase in risk between 1984 and 2000. The percent attributable risk also has increased with a median slope of 0.046 %/ppb per year (-0.087, 0.160), or a 56.1% increase over time, but the evidence for this assertion is weak ($p=0.4840$).

We note the unusually low risk estimate for nitrogen dioxide estimated in 1998. Reasons for this lower risk value are unclear but are neither due to the time series model formulation (degrees of freedom for the non-linear terms) nor the distribution of weather or air pollution concentrations. The tri-variate components of the Air Health Indicator were calculated excluding the information from 1998 (three right-hand panels of Figure 2). The median slope in concentration was insensitive to this single year exclusion (median slope of -0.296 ppb/year (-0.411, -0.255)) since the NO_2 concentrations in 1998 were not unusual. Exclusion of 1998 information, however, increased the risk from 4.180×10^{-5} log-mortality rate/ppb per year to 6.419×10^{-5} log-mortality rate/ppb per year (0.878, 11.519) with much stronger evidence of a positive median slope (p=0.0274). Sixteen additional models of risk were fit each excluding a single year of information. The risk trend line was most sensitive to the exclusion of 1998. The percent attributable risk median slope was 0.0839 %/ppb per year (-0.035, 0.0209) with weak evidence of a non-zero trend (p=0.1917). This trend in percent attributable risk corresponds to a 92.6% increase over the observation period. Thus the clear decline in NO_2 concentrations in Canada have not translated into health benefits as measured by mortality. This may be due to the fact that NO_2 is a marker of combustion for many sources and that the true toxic components of combustion have not declined at the same rate as NO_2.

Information concerning risk and time trend for each city can be visualized by plotting the time trend slope versus the shrunk risk among cities. This information is displayed in Figure 3 for ozone (top panel) and nitrogen dioxide (bottom panel) to illustrate this analysis feature. The trend line of the shrunk risks is plotted against the median of the annual shrunk risks by city. Most trend lines are negative (y-axis) except for very small positive slopes for Niagara and Winnipeg. The shrunk risks (x-axis) are all positive with about a 2 fold variation among cities.

The amount of shrinkage of risk is illustrated in the top two panels of Figure 4 which display the relationship between the estimates of the city-specific risks $\hat{\beta}_{ij}$ and the shrunk risks $\tilde{\beta}_{ij}$ by connecting the two estimates each year by a line with an arrow pointing in the direction of the pooled risk (solid line). The top left hand panel is for Regina, a relatively small Canadian city, and the top right hand panel is for Toronto, Canada's largest metropolitan community. It is evident from these graphs that the there is considerably more shrinkage of risk in the smaller community.

The middle and bottom two panels in Figure 4 display the shrunk risks annually (points), the city-specific trend line (solid line) and the pooled trend line (dashed line) for Winnipeg (middle left hand panel), Ottawa (middle right hand panel), Quebec (bottom left hand panel), and York (bottom right hand panel). These four cities were selected based on their relatively extreme values of either the trend line or shrunk risk visualized in Figure 3. First, there is considerable variation in the shrunk risks over time in each city. Second, although these cities represent the extremes in trend and risk it is not clear that there is any real difference in either trend or risk between these cites or from the pooled estimates. Formal statistical tests confirm that none of the cities show any evidence that their trend lines or shrunk risks are different from their pooled counterparts (p>0.2). Similar statistical tests on the nitrogen dioxide data drew the same conclusions as that for ozone.

4. DISCUSSION

In this paper we proposed a new method to estimate the association between daily variations in ambient air pollution and daily fluctuations in non-accidental mortality over space and time. Spatial-temporal risk estimates, coupled with city-specific and national estimates in trends in air pollution, can be used to assess whether the adverse effect of air pollution related to mortality have changed over time.

Within the Bayesian modeling framework, city-specific estimates of risk and the time trend in risk can be obtained. Cities can then be identified which display unusual spatial-temporal patterns in risk. Attempts to explain these patterns can be made in the second stage of the 2-stage modeling approach. Here, the annual average community specific risk estimates will be considered as the dependent variable and regressed on potential predictors of risk (community health status, air conditioning use, particle phase constituents, demographics, and measures of social welfare) within a Bayesian modelling framework over time and space. Non-linear models of air pollution association with mortality can also be considered. Risk may be also summarized by region of the country. The second stage model would contain two levels of clustering: city within region and region within the country. Trend estimates could then be obtained for the country and each region.

We are also interested in the longer term exposure effects on mortality. These effects are usually determined by examining cohorts of subjects followed over time in selected communities or neighbourhoods with varying long term air pollution concentrations (Pope et al., 2004). A dynamic risk model could be postulated including a time-air pollution interaction. However, due to the potential confounding of risk with age, a single static cohort cannot be used. In addition, ultimately all members of the cohort will die and thus time trends cannot be continually determined.

Health Canada is currently examining the effects of longer term outdoor pollution on longevity by using a cohort determined from linking income tax records to vital status and cancer incidence. A pilot study is underway in which over 600,000 residents of 10 Ontario communities have had their income tax records linked to both vital status and cancer incidence since the mid 1980s. Tax records report a subject's address, age, gender, marital status, and income annually. Information on additional mortality and cancer risk factors will be imputed partially from additional linkages with population based health surveys which contain information on smoking habits, diet, occupation, etc.

This income tax cohort can be dynamic in nature with all new fillings included each year. There is no time restriction on the monitoring of this type of cohort. The time-air pollution interaction can then be used as an estimator of temporal changes in risk. Careful attention must be paid, however, to the changing age-gender distribution of tax filers over time.

We have chosen not to include in the AHI an estimate of the number of people whose lives would have been lengthen, on average, if air quality would have been improved. Although such calculations have commonly been made for longer term exposure metrics in Canada (Coyle et al. 2003) using risks based on cohort studies (Krewski et al, 2003), they have not been attempted for risks based on time series studies for methodological reasons. The time series studies do not necessarily measure risk to individuals in the same manner as they do in cohort studies. Time series risks can be used in a similar manner to that of the cohort study based risks if one assumes that all members under study (in the time series case the entire population) have the same baseline hazard function and the same air pollution risk estimate at any given age (Miller and Armstrong, 2001; Burnett et al., 2003; Rabl, 2006). However, it is known that air pollution risk can vary by underlying disease status (Goldberg et al, 2005). The following argument identifies what is needed to perform such calculations.

Suppose we have a distribution at any given time t in the population of baseline hazard functions, relative risk associated with unit change in air pollution exposure, and personal exposure to air pollution. Let the joint hazard function of all three characteristics be denoted by $\lambda_p(t/\beta_p, x_p(t))$, where β_p is a real-valued scalar parameter representing the association between air pollution and mortality for the p^{th} individual in the population and $x_p(t)$ is the true value of personal exposure to pollution of the p^{th} individual at time t. For simplicity we assume a constant association of risk independent of time. We are interested in the population average hazard which is used to determine important quantities used in estimating number of deaths and years of life lost associated with changes in ambient pollution exposure. This population average hazard is given by

$$\lambda(t) = \int_{h_p} \int_{x_p} \int_{\beta_p} \lambda_p(t/\beta_p, x_p(t)) \partial \Im(\lambda_p, \beta_p, x_p), \tag{1}$$

where $\Im(\lambda_p, \beta_p, x_p)$ is the joint population distribution of the three characteristics of hazard, risk, and exposure. In practice, a proportional hazard function is often assumed of the form

$$\lambda_p(t/\beta_p, x_p(t)) = h_p(t) e^{\beta_p x_p(t)}, \tag{2}$$

where $h_p(t)$ is termed the "baseline" hazard function which is modulated by risk and exposure. A further simplifying assumption is that the three characteristics have independent distributions. That is, that one's underlying risk of death in general, the risk of dying due to air pollution exposure and the level of exposure are all mutually independent. In this case we can write the population average hazard function $\lambda(t)$ as

$$\lambda(t) = \int_{h_p} \int_{x_p} \int_{\beta_p} h_p(t) e^{\beta_p x_p(t)} \partial \Im_{\beta_p} \partial \Im_{x_p} \partial \Im_{h_p}. \tag{3}$$

The distributions $\Im_{\beta_p}, \Im_{x_p}, \Im_{h_p}$ are generally not known although we can get some idea of these distributions by studies of at risk populations to air pollution related deaths (diabetics and people with congestive heart failure for example), personal exposure studies, and disease specific life tables respectively. We can rewrite (3) in the form

$$\lambda(t) = \left(\int_{h_p} h_p(t)\partial\Im_{h_p} \right) \exp\left\{ \left(\int_{\beta_p} \beta_p(t)\partial\Im_{\beta_p} \right)\left(\int_{x_p} x_p(t)\partial\Im_{x_p} \right) \right\} \tag{4}$$

assuming the risk and exposure are sufficiently small to allow the approximation ($e^s = 1 + s$).

We do know, however, that the risk estimates from the time series studies can be viewed as arising from a dynamic cohort study with the following hazard function specification

$$h(t)e^{\beta x(t)}\ , \tag{5}$$

where $h(t)$ is a common baseline hazard to all subjects at risk at time t, β is a common risk parameter for all subjects, and $x(t)$ is the population-average exposure of all subjects at risk at time t (Burnett et al., 2003). In practice, this quantity is estimated as the average of pollutant concentrations from the available fixed site monitoring data in a community.

From Burnett et al. (2003) we know that

$$x(t) = \int_{x_p} x_p(t)\partial\Im_{x_p}\ , \tag{6}$$

and after setting

$$h(t) = \int_{h_p} h_p(t)\partial\Im_{h_p} \text{ and } \beta(t) = \int_{\beta_p} \beta_p(t)\partial\Im_{\beta_p}\ , \tag{7}$$

we can see that the risk estimate from the time series studies can be used in conjunction with the baseline hazard estimated form life tables and estimates of changes in population average personal exposure to determine years of life lost and the excess number of deaths over a fixed time period associated with modelled changes in ambient air pollution. Furthermore, under the trivial condition that hazard and risk do not vary among population members, the quantities (3) and (4) are equivalent and thus again the time series risk estimates can be coupled with life tables of the general population to determine years of life lost (Miller and Armstrong, 2001; Burnett et al., 2003; Rabl, 2006).

However, we know that the distributions of the three characteristics (hazard, risk, and exposure) are not independent. For example, persons with diabetes and cardiovascular diseases have a higher relative risk for air pollution related mortality than the general population (Goldberg et al., 2005). Further, subjects with pre-existing diseases may spend more time indoors and thus have less exposure to outdoor air pollutants than the general population.

Thus we are interested in the joint distribution of the three characteristics $\Im(\lambda_p, \beta_p, x_p)$ and how far apart the two quantities

$$\int_{h_p}\int_{x_p}\int_{\beta_p} h_p(t)e^{\beta_p x_p(t)}\partial\Im(\lambda_p, \beta_p, x_p)$$

and (8)

$$\left(\int_{h_p} h_p(t)\partial\Im_{h_p} \right) \exp\left\{ \left(\int_{\beta_p} \beta_p(t)\partial\Im_{\beta_p} \right)\left(\int_{x_p} x_p(t)\partial\Im_{x_p} \right) \right\},$$

can be for selected joint and marginal distributions. The first quantity in (8) will be greater than the second quantity if the distributions have positive support with the difference in magnitude between the two depending on the degree of positive correlation between the distributions and the amount of skewness to the right.

It is not possible to determine an individual's risk or baseline hazard function and thus not possible to determine the true joint distribution of these quantities. However, we can estimate underlying hazard functions and risk for specific subgroups of the population. For example, Goldberg et al. (2005) have established a dynamic population study in the city of Montreal, Canada. All interactions with the provincial health care system for subjects over 65 years of age are recorded and linked to the individual over time, such as doctors' billings, emergency visits and hospital admissions, drug prescriptions, clinic visits, and vital status. The population can then be divided by presence of one or more chronic diseases. Time series of deaths for all non-accidental causes can then for created for each subgroup and linked to air pollution using time series statistical methods. Thus a disease-specific risk can be determined. The total attributable risk (sum of disease specific risk times number of daily non-accidental deaths in that disease group) can be compared to the equivalent quantity based on the total number of non-accidental daily deaths times the risk based on a time series of total deaths. The difference in these two quantities would give an indication of the degree of under(over)estimation of attributable risk using the standard time series risk. Disease-specific life tables would then be required to translate the disease-specific air pollution risks into years of life lost and number of individuals expected to survive a fixed time period under selected changes in ambient air pollution.

We note that for cohort studies of long-term air pollution exposure and mortality, each subject is assigned an exposure, thus one does not need to integrate over the distribution of personal exposures. In practice however, exposures are developed and assigned to geographic areas. All cohort members are given the same exposure that live in that area.

Cohort studies are often analyzed using the proportional hazard model such as that given by (5). Here, a common baseline hazard is postulated for all subjects under observation. This assumption is clearly violated since each subject is expected to have a unique hazard formulation. However, we are only interested in modeling the hazard function over long time periods since the air pollution exposure metric is defined in that manner. The magnitude of ones hazard in a frail group near death is not of interest. Thus each subjects' hazard is expected is vary smoothly over long time frames (on the order of years or decades). The variation in hazard functions between subjects is also expected to be much less in the cohort framework than in the time series model for which the hazard function needs to be modelled on much shorter time frequencies (in the order of days). Variation in the baseline hazard functions between subjects can also be reduced by controlling for several individual mortality risk factors such as smoking habits, diet and disease history, which can vary over time.

The same reasoning can be applied to the risk function distribution. Air pollution mortality risk will clearly vary among the cohort members. The between subject variation in risk is expected to be much smaller than that obtained by the short-term exposure based time series design, at least at the commencement of the cohort study in which most subjects are relatively healthy. Variation in risk between groups of subjects can be accounted for in the cohort survival model by considering interactions between personal risk factors for mortality and air pollution.

The two quantities in (8) will be close if the dispersion of the hazard and risk distributions is small. In this case it is reasonable to use the risk estimates based on the cohort studies, in conjunction with disease-specific life tables, to determine the number of excess deaths and years of life lost associated with changes in ambient air pollution due to implementation of regulations.

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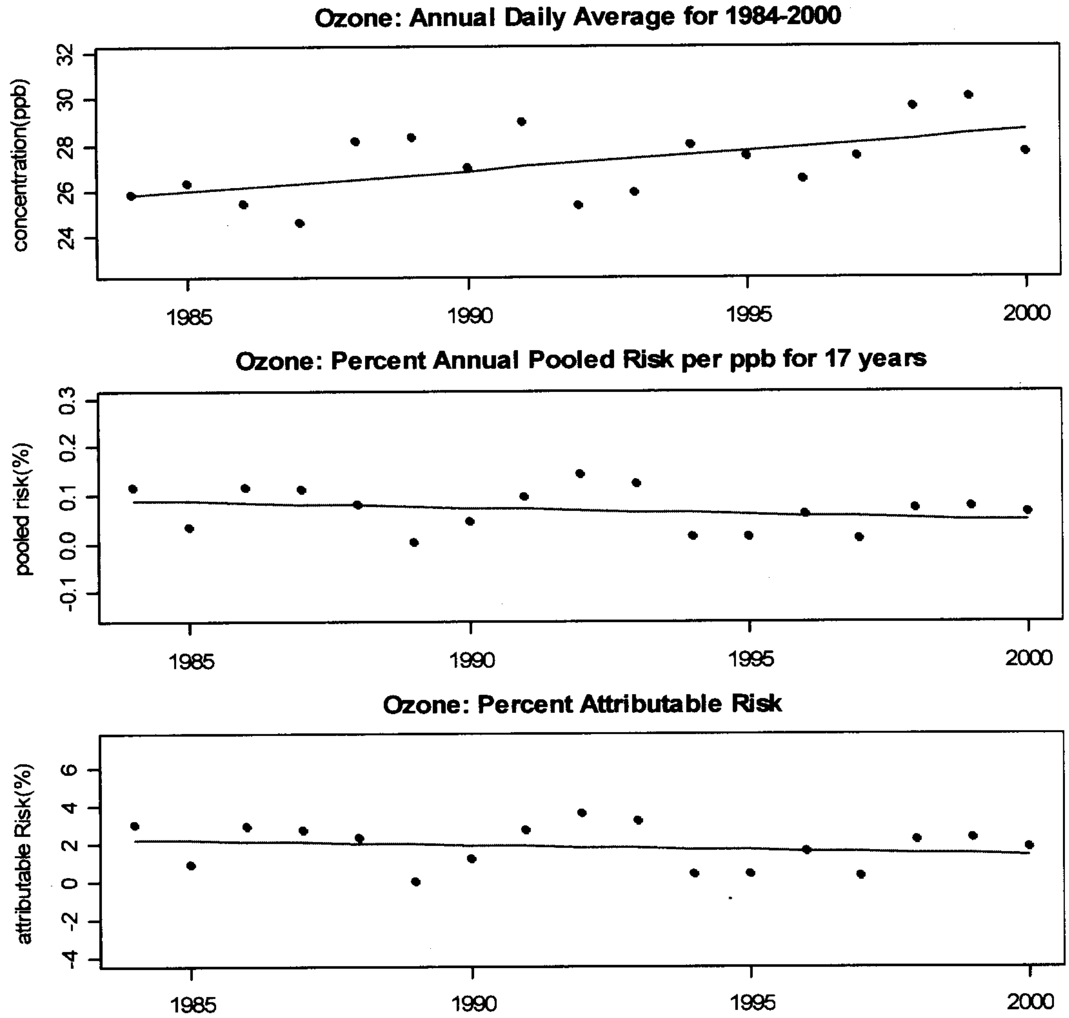

Figure 1. Annual concentrations of ozone over 24 Canadian cities with trend line (top panel), annual ozone-mortality unit risk x 100 and trend line (middle panel), percent attributable risk – product of concentration and risk x 100 – and trend line (bottom panel).

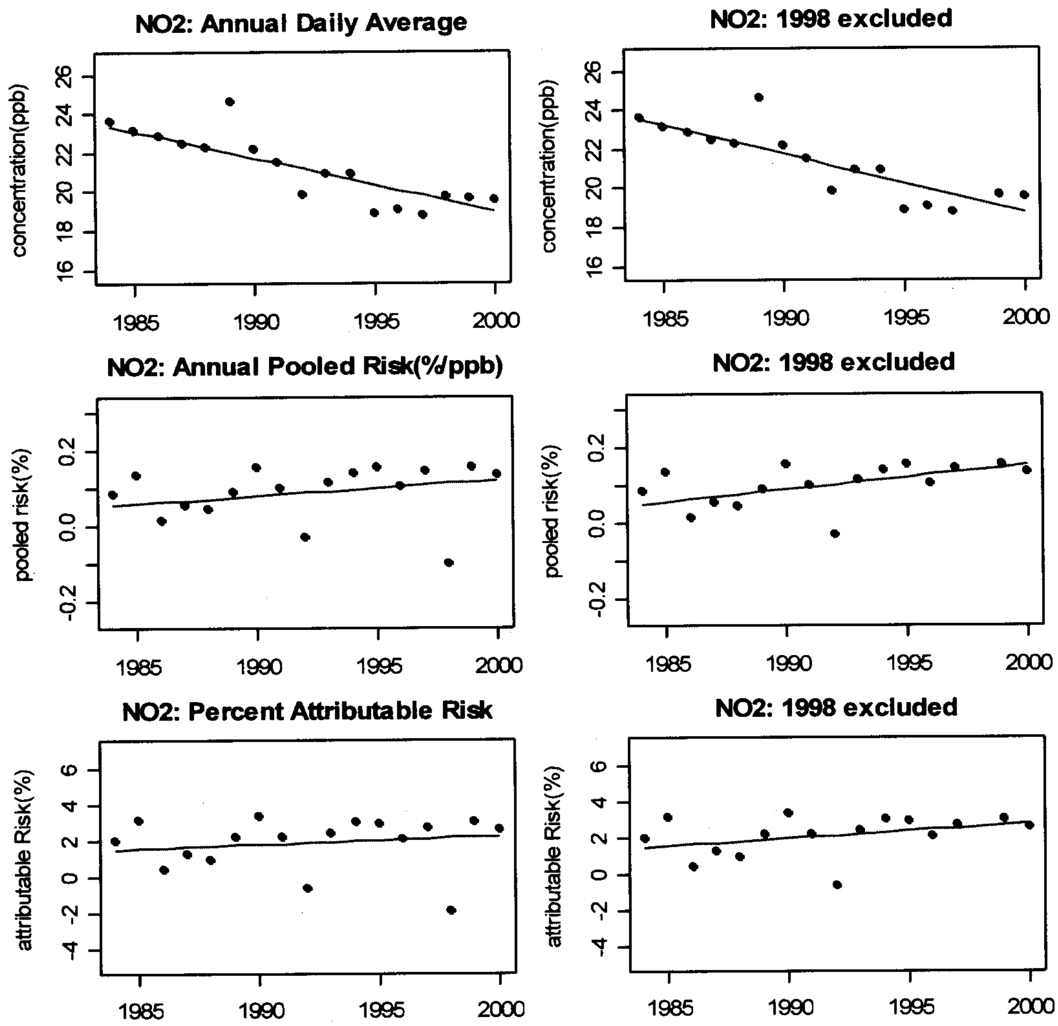

Figure 2. Annual concentrations of nitrogen dioxide over 24 Canadian cities with trend line (top left panel), annual nitrogen dioxide-mortality unit risk x 100 and trend line (middle left panel), percent attributable risk – product of concentration and risk x 100 – and trend line (bottom left panel). Right panels are corresponding plots excluding the data for 1998.

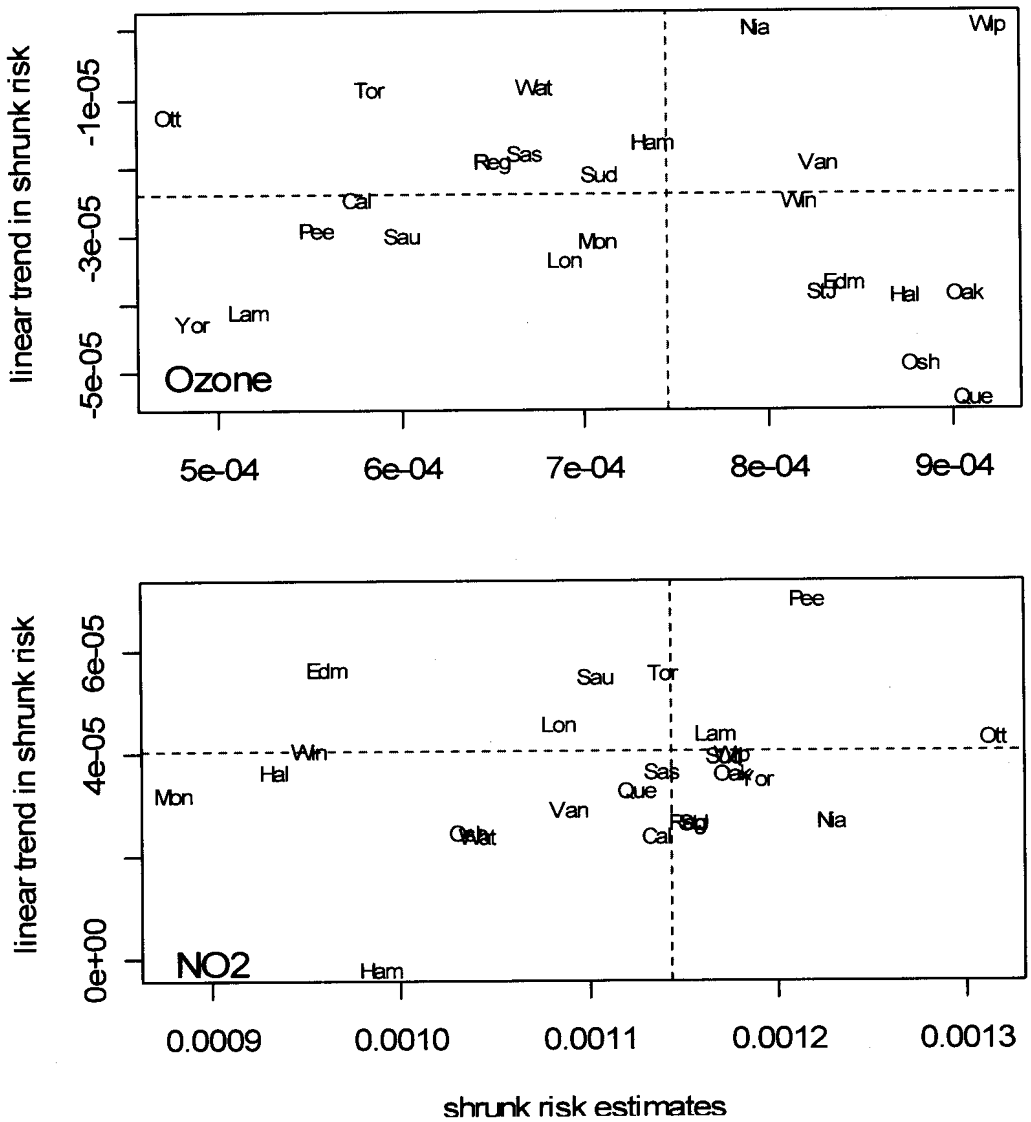

Figure 3. City-specific median trend line (y-axis) of shrunk risks and median of annual city-specific shrunk risks (x-axis) for ozone (top panel) and nitrogen dioxide (bottom panel). City names indicated on plot. Pooled risk estimate represented by vertical dashed line and pooled linear trend estimate represented by horizontal dashed line.

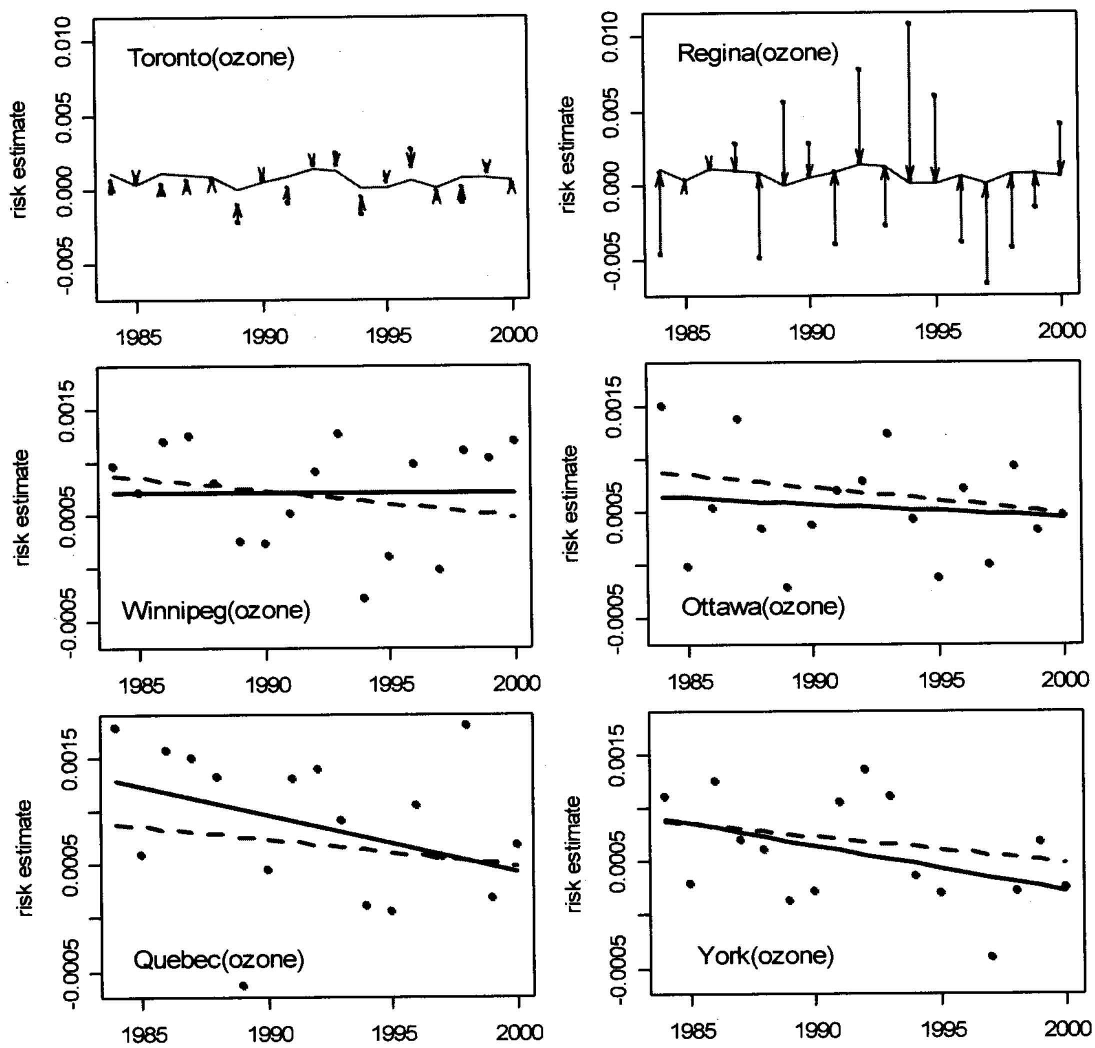

Figure 4. City-specific ozone risks and shrunk risks (connected by arrowed line), and pooled risk (solid line) for Toronto (upper right hand panel) and Regina (upper left hand panel). Ozone median time trend slope of city-specific shrunk risks (solid line), shrunk risks (points), and pooled time trend line (dashed line) for Winnipeg (middle right hand panel), Ottawa (middle left hand panel), Quebec (lower right hand panel), and York (lower left hand panel).

ANNEX C
Workshop on Methodologies for Environmental Public Health Tracking of Air Pollution Effects – January 15-16, 2008
Agenda

Day one

Registration and continental breakfast		7:30-8:00
Welcome and Introductions		8:00-8:10
Problem Statement and Charge	Tom Matte	8:10-8:20
Overview of agenda and process	Jon Samet	8:20-8:30
EPHT Context		
EPHT air pollution health tracking overview and New York example	Valerie Haley	8:30-8:50
ED visits for asthma and ambient ozone in Maine	Chris Paulu	8:50-9:00
Air quality data sources for EPHT	Fred Dimmick	9:00-9:15
Communicating air quality health impacts to stakeholders	Dan Wartenberg	9:15-9:30
Q and A		9:30-9:40
Break		9:40-9:50
Methodology		
Ozone and $PM_{2.5}$ data in exposure assessment	Warren White	9:50-10:05
Statistical issues in health impact estimates at the state and local level	Montserrat Fuentes	10:05-10:20
Use of external CR functions for local scale health impact estimates	Bryan Hubbell	10:20-10:35
Measuring public health accountability of air quality management	Richard Burnett	10:35-10:50
Q and A		10:50-11:00
Examples		
The EC APHEIS project	Sylvia Medina	11:00-11:15
Chronic $PM_{2.5}$ health impact assessment in European cities	Michal Krzyzanowski	11:15-11:30
Small area health impact assessment	Jon Levy	11:30-11:45
London's congestion charging / low emission zone programs – impact assessment	H Ross Anderson	11:45-12:00
Q and A		12:00-12:10
Lunch		12:10-1:10
Working group assignments	Jon Samet/A Cohen/ Tom Matte	1:10-1:15
Working groups meet (break as needed)	Chairs/rapporteurs	1:15-6:00
Objective1 – Use of local analyses	Thomas Louis/Jeremy Sarnat	
Objective 2 – Use of external CR function estimates	John Balmes/Fuyuen Yip	
Objective 3 – Communications approaches	John Bachmann/Nicholas Jones	
Group dinner (optional)		7:30

Day 2

Progress and clarification of group charges	Jon Samet	8:00-8:15
Working groups meet (break as needed)		8:15-12:30
Lunch		12:30-1:30
Working groups meet		1:30-2:30
Working groups report back and discussion	Jon Samet and Working Group Rapporteurs	
Objective 1	Jeremy Sarnat	2:30-3:15
Break		3:00-3:15
Objective 2	Fuyuen Yip	3:15-4:00
Objective 3	Nicolas Jones	4:00-4:45
Concluding remarks and next steps	Jon Samet/Tom Matte/Aaron Cohen	4:45-5:00