Performing Local-Scale Health Impact Assessments with Near-Field Air Quality Modeling

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1. INTRODUCTION

The availability of near-field air quality modeling creates the opportunity to perform local scale health impact analysis and also poses special challenges. It is important to match the scale of the air quality data with spatially resolved human health data, including effect estimates and baseline incidence rates. Such matching can be problematic, as local scale health data are frequently not available, or spatial cover is incomplete. In this paper we examine techniques for performing local health impact analyses, using a recent analysis in Detroit as an example.

2. OVERVIEW OF NATIONAL HEALTH IMPACT METHODS

There are four key components to typical health impacts estimation:

1. Estimate a change in 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[1] 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.

The health impact function described in step three estimates the change in a health outcome, such a chronic bronchitis, for a particular population exposed to some level of air pollution. A typical health impact function might look like:

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

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.

3. ANALYTICAL CHALLENGES TO SCALING DOWN HIA FROM NATIONAL TO LOCAL LEVELS

Traditional EPA benefits assessments have used coarse-scale health and air quality input data to assess the health impacts of national-scale regulatory interventions. Such analyses produce national-scale data that would be problematic to report at higher resolutions. For any given location, national-scale data is unlikely to describe local-scale health impacts.

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[1] 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".

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 that may rely on the same national-scale inputs. Below we discuss the challenges to developing each data input.

3.1 Air Quality Modeling

The changes in modeled or monitored air quality ultimately drive the health impact assessment. It may be possible to provide air quality estimates by employing near-field dispersion modeling. Alternately, it may be possible to combine dispersion and photochemical grid modeling. Because this paper focuses on the development of health data to perform local impact assessments, we do not further elaborate on air quality modeling techniques here except to note that the resolution of the estimated air quality change has a direct effect on the resolution of the exposure estimates.

3.2 Develop Effect Estimates

The effect estimate relating changes in air pollution exposure to adverse health effects should adequately describe this relationship for the specific location analyzed. National multi-city estimates may or may not suffice when performing an urban scale analysis. The demographics, health status and exposure patterns of local populations may differ significantly from those analyzed in national-scale epidemiology studies. However, effect estimates specific to the area of interest may not be available. Or, the smaller populations observed in local scale analyses may yield effect estimates that lack sufficient statistical power to be useful.

When performing a national-scale analysis, EPA frequently employs meta-analysis and pooling techniques. Under this approach, studies are weighted by the inverse of their variance. This particular technique gives more weight to studies with smaller variances. The pooling approach can generate a more robust national effect estimate, but it is less useful for generating local effect estimates because it does not address the inherent heterogeneity in populations and exposures across areas.

More recent ozone (Stieb et al., 2002; Bell et al., 2004; Bell et al, 2005; Ito et al, 2005, Levy et al, 2005) and PM (Levy et al., 2000; Stieb et al., 2002; Dominici et al., 2003; Franklin et al., 2007) epidemiology studies have attempted to examine the variability in effect estimates across cities to determine whether 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.

Detroit is among those areas where city-specific estimates are available. Several ozone (Bell et al., 2004; Schwartz, 2004; Huang et al. 2004; Ito 2003) and PM (Ito, 2003) epidemiology studies have generated effect estimates specific to Detroit. These studies estimate the change in ozone-related premature mortality and respiratory hospitalizations and PM-related respiratory hospitalizations. While these studies offer city-specific estimates, several estimates suffer from poor statistical power. Moreover, these studies do not cover the full suite of health endpoints typically assessed in a benefits analysis.

Considering the trade-offs described above, 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. Finally, in cases where local estimates lack statistical power, it may be best to apply national effect estimates.

3.3 Baseline Incidence Data

Unlike with effect estimates, it is likely that substantial local baseline incidence data could be available for at least some health outcomes. 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.

Figure 1 demonstrates the importance of applying local scale incidence rates. This figure shows how 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).

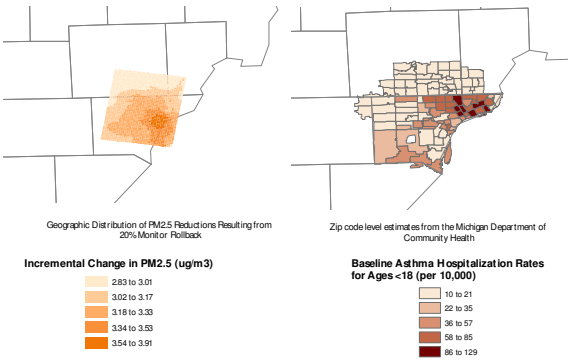

Fig. 1. Comparison of the Geographic Distribution of Zip-Code Level Asthma Hospitalization Rates and a Hypothetical 20% Reduction in Monitored $PM_{2.5}$ in the Detroit Metropolitan Area

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 (90th percentile confidence interval from 17 to 54). In contrast, using the local-scale rates produces a reduction in asthma-related hospitalizations of 53 cases (90th percentile confidence interval from 26 to 81). Clearly, using national-scale baseline incidence rates would underestimate 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 which covers Detroit, it was necessary for an epidemiologist to reformat these data to generate tables in a format suitable for use in a health impact assessment.

4. UNCERTAINTIES AND LIMITATIONS TO LOCAL HIA

The traditional approach to characterizing uncertainty in the HIA has been to use the standard error associated with the effect estimate to generate confidence intervals. However, such an estimate only describes a narrow range of the total uncertainty. There is no comparable information available for the remaining impact function elements, including the baseline incidence rates, exposure estimates and air quality changes.

For the reasons described in the preceding sections, the local HIA imposes additional uncertainties—which are in turn difficult to characterize quantitatively. Thus, the local HIA is effected by the same uncertainties as the national assessment and also introduces key uncertainties. Sensitivity analyses, which vary key input parameters such as effect estimates and baseline incidence rates—may be a useful substitute. Finally, to some extent these uncertainties may be mitigated by careful selection of input data, particularly effect estimates.

5. REFERENCES

List all bibliographical references at the end of the abstract in alphabetical order by first author. When referring to them in the text, type the corresponding author surname(s) followed by the year of publication—for example, O'Possum and Platypus (1984). Please use the referencing style from any of the American Meteorological Society (AMS) journals, which is explained in brief on p. 3 of http://www.ametsoc.org/PUBS/Authorsguide/pdf_vs/agbrf2002.pdf and in more detail at http://www.ametsoc.org/pubs/refstyl.html).

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