Identifying "At-Risk" Populations: Applying High Resolution Air Quality, Demographic and Baseline Health Data to Define and Locate At-Risk Populations

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Introduction

In 2004 the National Research Council (NRC) report "Air Quality Management in the United States (2004)" recommended that the U.S. EPA transition from a pollutant-by-pollutant approach to air quality management to a multi-pollutant, risk-based approach . . ." In response, EPA selected the Detroit metropolitan area as a test bed to evaluate **multi-pollutant, risk-based approaches** to air quality management. This overall goal of this analysis was to: (1) demonstrate a framework with available technical tools, methods and data that implemented and evaluated multi-pollutant, risk based control strategies; and (2) evaluate the benefit of implementing such a framework as compared to a single-pollutant, SIP-based approach to air quality management.

As part of this analysis, we simulated two contrasting air quality management strategies. While both met PM2.5 and ozone air quality targets, one strategy reflected a "status quo" approach where controls are selected separately to address ozone and $PM_{2.5}$ nonattainment at monitor locations, while the other strategy reflected a "multi-pollutant, risk-based" approach aimed at further reducing population risk from exposure to ozone, PM2.5 and selected air toxics while still addressing ozone and $PM_{2.5}$ nonattainment.

By considering local air quality, demographic and health data jointly, we:

- Achieved the same or greater reductions of $PM_{2.5}$ & O_3 at monitors as a status-quo strategy
- Improved air quality regionally and across the urban core for O_3, $PM_{2.5}$ and selected air toxics
- Produced approximately 2x greater benefits for $PM_{2.5}$ and O_3 as compared to a status-quo strategy
- Reduced non-cancer risk

Figure 1 shows the locations of key point sources in Detroit and the incremental change in $PM_{2.5}$ air quality between strategy the status-quo and multi-pollutant risk-based strategies. The latter strategy achieves greater incremental air quality improvements in the most populated portion of the urban core.

Having utilized these local scale data to demonstrate how multi-pollutant, risk-based approaches can maximize air quality benefits across the population of Detroit, we next wanted to assess the change in air pollution health impacts among those populations most vulnerable and susceptible to air pollution. Specifically, we aimed to answer the following questions:

1. **Where are the populations most vulnerable to air pollution and susceptible to air pollution health impacts located?**
2. **To what extent does the multi-pollutant, risk-based air quality management plan benefit these populations?**

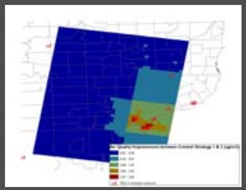
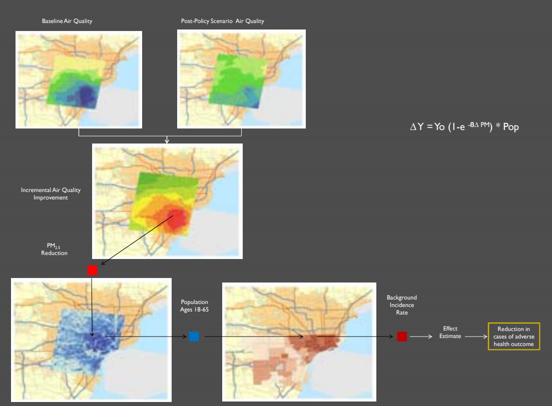


Figure 1: Incremental change in annual mean $PM_{2.5}$ levels between control strategy 1 and 2

Materials and methods

Figure 2 below illustrates graphically the key steps in a criteria pollutant health impact assessment (HIA). Software packages including the environmental Benefits Mapping and Analysis Program (BenMAP) relate changes in air quality, population exposure risk estimates and baseline incidence estimates to calculate a change in health impacts.



The finer the spatial scale of these key inputs, the more useful they may be to the Environmental Justice analysis. **Figures 3, 4 and 5** illustrate how fine-scale air quality, population distribution and baseline health status can reveal the location of populations at greatest risk of air pollution health impacts.

Figure 3: African-American males aged 0-17 at 1km cells

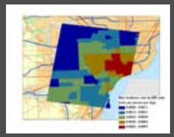


Figure 4: Hospitalization rate among all children aged 0-17 at ZIP codes

Figure 5: Distribution of baseline $PM_{2.5}$ air quality levels at 1km cells

As we demonstrate below, these fine-scale data may be used to identify populations most vulnerable and susceptible to air pollution. In **Figure 7** we have multiplied the population in figure 3 against the hospitalization rate in figure 4 to create a map of the population-weighted hospitalization rate. The red outline identifies those areas that are at or above the 75th percentile or higher of the population-weighted hospitalization rate (i.e. populations most **susceptible**). **Figure 7** identifies areas in which baseline $PM_{2.5}$ levels are at or above the 75th percentile of $PM_{2.5}$ exposure (i.e. populations most **vulnerable**). Finally, **Figure 8** joins these two maps to identify populations most **vulnerable and susceptible**.

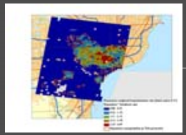


Figure 6: Populations susceptible to air pollution

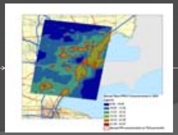


Figure 7: Populations vulnerable to air pollution

Figure 8: Populations vulnerable and susceptible to air pollution

Results

Table 1 below summarizes the per-person change in $PM_{2.5}$ across the total population, black non-hispanics, Asian non-hispanics and white non-hispanics. The per-person change in $PM_{2.5}$ is consistently larger using 1km air quality modeling. The multi-pollutant, risk-based strategy demonstrates the largest per-person change across all populations as well as minority populations.

Table 2 presents the per-person change in $PM_{2.5}$ exposure among vulnerable and susceptible populations (identified in **Figure 8**) and among the rest of the population. The multi-pollutant, risk-based approach produces the largest per-person change in $PM_{2.5}$ exposure among vulnerable and susceptible populations.

Table 1: Per-person change in $PM_{2.5}$ by scenario and air quality modeling resolution

	Status-quo approach			*Multi-pollutant, risk-based approach*		
	12km resolution	1km resolution	% Difference	12km resolution	1km resolution	% Difference
Total Population	0.249	0.271	8%	0.706	0.721	2%
Black Non-Hispanic	0.249	0.258	3%	0.802	0.803	<1%
Asian Non-Hispanic	0.254	0.282	10%	0.626	0.652	4%
White Non-Hispanic	0.249	0.278	10%	0.613	0.658	7%

Table 2: Per-person change in $PM_{2.5}$ among populations vulnerable and susceptible to air pollution impacts

	Per-person change in $PM_{2.5}$ exposure	
	Among susceptible and vulnerable populations	*Among rest of population*
Status-quo strategy	0.33	0.28
Risk-based, multi-pollutant strategy	1	0.5
Percentage change	***300%***	***180%***

Conclusions

Integrating spatially resolved information regarding air quality data, population demographics and baseline health statistics can allow analysts to identify those populations most vulnerable and susceptible to air pollution impacts. These data may then be used to inform air quality management strategies designed to maximize air pollution benefits among these populations.

Using Detroit as a pilot, we demonstrated how following this approach resulted in air quality strategies that produced benefits among both the total population as well as among those individuals at greatest risk of air pollution-related health impacts.

While in this analysis we used asthma hospitalization rates and $PM_{2.5}$ air quality levels to define vulnerable and susceptible populations, alternate criteria are possible. Susceptibility might alternately be defined using asthma prevalence rates or hospitalization rates for other key health endpoints including cardiovascular endpoints. Vulnerability might be defined using ozone or air toxic air quality levels. The approach described above can be readily adaptable to use the local fine-scale data available.