

Comparing Exposure Metrics for the Effects of Fine Particulate Matter on Emergency Hospital Admissions

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CMAS - Chapel Hill

Oct 30, 2013



Motivation

Numerous studies have shown the positive association between short and long term exposure to particulate matter and adverse human health effects:

Dominici, Peng and Bell; Pope et al; Bell et al; and Ostro et al for respiratory effects - among others.

Goal

A crucial step in an epidemiological study of the effects of air pollution is to **accurately quantify exposure** of the population. We investigate the sensitivity of the health effects estimates associated with short-term exposure to fine particulate matter with respect to three potential metrics for daily exposure:

- ▶ Ambient monitor data (**AQS**)
- ▶ Estimated values from a deterministic atmospheric chemistry modeling system - Community Multi-scale Air Quality (**CMAQ**)
- ▶ Stochastic daily average human exposure simulation output (**SHEDS**)

Metrics

Strengths & Weaknesses of each metric:

- ▶ AQS is readily available, but is incomplete over space and time
- ▶ CMAQ is spatially and temporally complete, but has different sources of uncertainty due to boundary conditions, mathematical approximations, and parameterizations of physical models.
- ▶ SHEDS-PM estimates account for human activity patterns and variability in pollutant concentration across microenvironments, but requires extensive input information and computation time.

SHEDS

SHEDS: population exposure model for PM developed by EPA.

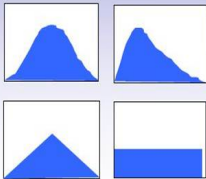
- ▶ Probabilistic approach to estimate distributions of inter-individual variability in outdoor and indoor microenvironmental PM_{2.5} exposures for a simulated population based on ambient air quality and human activity data (Burke 2009): ie workplace or residential environment; exposure through cooking & smoking.
- ▶ Human activity data based on the Consolidated Human Activity Database (CHAD): over 22,000 daily dairies

SHEDS

Input Databases

- Census
- Human Activity
- PM Concentrations

Exposure Factor Distributions

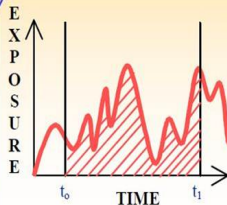


Algorithms

- Generate Population

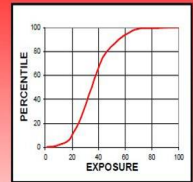


- Calculate Individual Exposure/Dose Profile

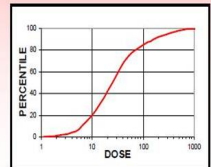


Output

- Population Exposure



- Population Dose



Metrics

- ▶ CMAQ serves as a surrogate for directly measuring ambient pollution exposure
- ▶ SHEDS-PM is a surrogate for population exposure to fine particulate matter
- ▶ SHEDS-PM can provide information about short-term population ambient exposure.

Metrics

- ▶ Limitation of many studies of adverse human health effects is a single exposure value is used for all individuals whereas personal exposure can vary greatly.
- ▶ While direct measurements of individual exposure are not available with sufficient spatial and temporal coverage to enable comparison with health effects data at the scale evaluated here, SHEDS-PM estimates population distributions of inter-individual variability in daily average exposure using information about human activity patterns and living environments, as well as census data.

Comparison

- ▶ We consider a case study of the association between $PM_{2.5}$ and emergency hospital admissions for respiratory cases (RESP) for the Medicare population (ages 65 and older) across three counties in New York.
- ▶ Particular interest: quantify the impact and/or benefit to using SHEDS to measure exposure to $PM_{2.5}$.

Respiratory admissions were classified based on ICD-9 codes including chronic obstructive pulmonary disease (490-448) and respiratory tract infections (464-466, 480-497) Peng et al, 2008.

Hospital admissions available on a county level, thus AQS, CMAQ, and SHEDS-PM aggregated to county level.

Confounders

- ▶ Many studies (Dominici 2000, Dominici 2002, and Peng et al 2006) have illustrated potential confounders and the importance of adjusting for these effects.
- ▶ We employ the semi-parametric method outlined in Peng et al 2006 to adjust for seasonal and long-term trends by incorporating natural splines and smooth functions of time.
- ▶ Weather variables such as temperature and relative humidity are also considered confounders.
- ▶ A confounding term is included for the 1-day lag for ozone, as well as temperature where the mean value is taken over the preceding 3-day period.

Terminology and Notation

- ▶ Y_t as the total number of events on day t across all three counties.
- ▶ linear and quadratic fit in t
- ▶ spline fits in max daily temperature (temp_t) and ave daily relative humidity (hum_t).

Additional non-pollutant confounders considered

- ▶ temp lag: ave temp over previous 3 days ($\overline{\text{mean}(\text{temp})}_t$)
- ▶ ozone
- ▶ day of week (dow): 6 levels with Sat as baseline exposure.

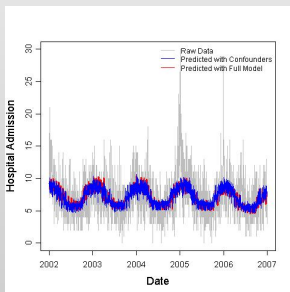
Ambient Exposure Model: Base Model - Seasonal Effects and Confounders

The counts are modeled as Poisson in the base model (no exposure effect):

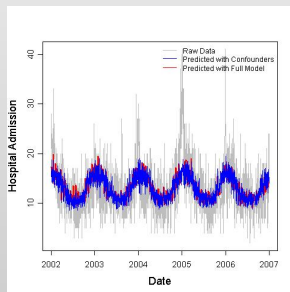
$$\begin{aligned}\log[E(Y_t)] &= \log N_t + \beta_0 + s(\text{temp}_t; d_1) + s(\overline{\text{hum}}_t; d_2) + \beta_1 t + \beta_2 t^2 \\ &+ \beta_3 \overline{\text{mean}(\text{temp})}_t + \beta_4 \text{ozone}_t + \beta_{\text{dow}} \text{dow}_t\end{aligned}$$

Assumes that there are no interactions between covariates, and includes an offset term for Poisson models, $\log N_t$

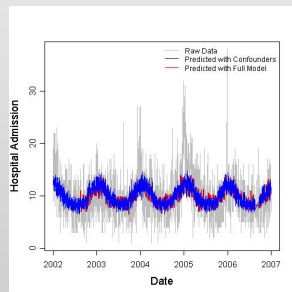
Base Model Fits



(a)



(b)



(c)

Base Model and AQS Fits: (a) Bronx, (b) Queens, & (c) New York County. Utilizing a generalized linear model fit, the blue lines show the effect of the confounders on emergency respiratory admissions.

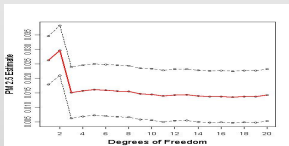
Ambient Exposure Model: AQS and CMAQ

For AQS and CMAQ metrics, the counts are modeled as Poisson with a term capturing ambient exposure:

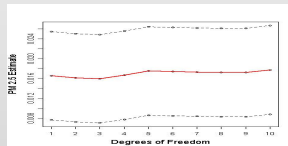
$$\begin{aligned}\log[E(Y_t)] &= \log N_t + \beta_0 + s(\text{temp}_t; d_1) + s(\overline{\text{hum}}_t; d_2) + \beta_1 t + \beta_2 t^2 \\ &+ \beta_3 \overline{\text{mean}(\text{temp})}_t + \beta_4 \text{ozone}_t + \beta_{\text{dow}} \text{dow}_t \\ &+ \beta_{PM} PM_t\end{aligned}$$

β_{PM} represents the effect of ambient exposure for change in exposure PM at time t

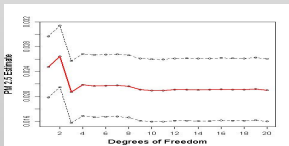
Spline Sensitivity Analysis



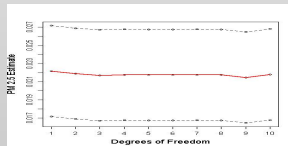
(a)



(b)



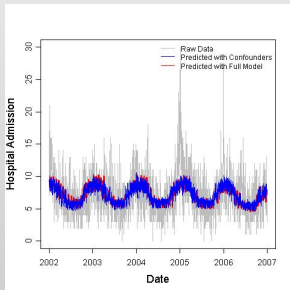
(c)



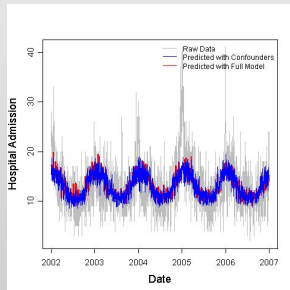
(d)

Spline sensitivity analysis over all counties for temperature (a) and relative humidity (b) on PM coefficient for AQS; temperature (c) and relative humidity (d) on PM coefficient for CMAQ.

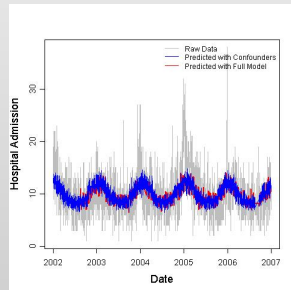
Base Model Fits and AQS



(a)



(b)



(c)

Base Model and AQS Fits: (a) Bronx, (b) Queens, & (c) New York County. Utilizing a generalized linear model fit, the blue lines show the effect of the confounders on emergency respiratory admissions, and the red indicates the added effect of ambient $PM_{2.5}$.

Personal Exposure Model: SHEDS-PM

- ▶ Analysis incorporating estimated personal exposure is approached differently, as the SHEDS-PM personal exposure model allows us to consider exposure at an individual level
- ▶ Reich, Fuentes, and Burke (2009) introduce a Bayesian model that incorporates the exposure distributions to account for variability in exposure across the population, which is the methodology considered here.

Personal Exposure Model

Reich et al 2009:

$$\begin{aligned}\log[E(Y_t)] &= \log N_t + \beta_0 + s(\text{temp}_t; d_1) + s(\overline{\text{hum}}_t; d_2) + \beta_1 t + \beta_2 t^2 \\ &+ \beta_3 \overline{\text{mean}(\text{temp})}_t + \beta_4 \text{ozone}_t + \beta_{\text{dow}} \text{dow}_t \\ &+ \alpha_{PM} m_{t-1} + \frac{1}{2} \alpha_{PM}^2 v_{t-1}\end{aligned}$$

- ▶ α_{PM} represents the change in individual exposure
- ▶ $\alpha^2 v_t$ accounts for variation in exposure across the population.
- ▶ m_{t-1} is the lag-term for the mean personal exposure, as indicated by Braga, 2001.

Model: SHEDS-PM

Consider the term for mean personal exposure in the individual model:

$$\alpha_{PM} m_{t-1} + \frac{1}{2} \alpha_{PM}^2 v_{t-1}$$

Note: If variance of the exposure distribution is zero, this reduces to the ambient concentration model with exposure $PM_t = m_{t-1}$.

Bayesian Framework

- ▶ A Bayesian analysis begins by specifying a prior distribution for each model parameter, which quantifies the information about parameter before observing the data.
- ▶ After observing the data, we have two sources of information, the data's likelihood and the prior, which are combined using Bayes theorem to give the posterior distribution
- ▶ The **posterior distribution** represents the current state of knowledge based on all available information and is used for inference.
- ▶ We are interested in the posterior distribution of the exposure coefficient (β_{PM}) for inference about ambient versus personal exposure

Simulation

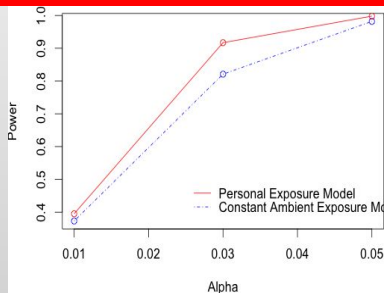
A simulation study is conducted to test the **power of detecting a relative risk signal** from the three exposure metrics defined above.

Z , simulated health data, generated using random draws from a Poisson distribution with a linear mean function in the confounders, simulated values for the daily mean exposure M_t , and specified values for the variance V of the daily individual exposures.

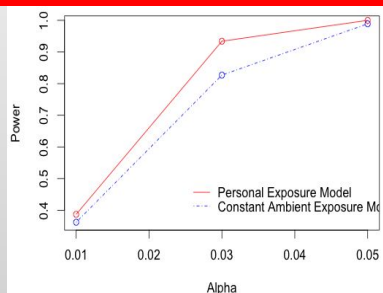
Simulation

- ▶ For each metric, test the null hypothesis that the $PM_{2.5}$ effect on the relative risk is zero
- ▶ The power of detecting the individual effect α with the distributional component $\frac{1}{2}\alpha^2 V$ is compared to the power of detecting the effect β_{PM} of $PM_{2.5}$

Simulation Results



(a)



(b)

Power across $\alpha = 0.01, 0.03, 0.05$. V fixed at 0.3 (a) and 1.0 (b). The red solid line represents the personal exposure metric SHEDS; blue dashed line is ambient AQS.

V	$\alpha=0.01$		$\alpha=0.03$		$\alpha=0.05$	
	PE	Amb	PE	Amb	PE	Amb
0.3	0.395 (0.012)	0.373 (0.012)	0.917 (0.007)	0.821 (0.010)	0.998 (0.001)	0.982 (0.003)
1	0.387* (0.012)	0.362 (0.012)	0.934 (0.006)	0.827 (0.009)	1.000 (0.000)	0.989 (0.003)

SE's are in parenthesis, * indicates significance at the 0.05 level, and **bold** indicates significance at the 0.01 level

Simulation Results

- ▶ As the strength of the effect for $PM_{2.5}$ increases, model incorporating individual exposure has greater power than model utilizing ambient AQS data.
- ▶ Difference in power significant for the most realistic scenario for the observed dependence between AQS and SHEDS.

Model Validation

- ▶ Sensitivity analysis indicates that confounding factors such as temperature and time were satisfactorily addressed.
- ▶ The simulation study shows that SHEDS-PM exhibits a higher power for detecting an increase in relative risk than AQS and CMAQ, with power increasing as a function of the true magnitude of the relative risk coefficient.
- ▶ Several reasonable values for the prior variance were considered to test prior robustness with similar results.

Results: AQS, CMAQ and SHEDS-PM

Showed a positive association between increased exposure and number of admissions for all metrics.

Both the AQS and CMAQ exposure metrics exhibit a positive coefficient for $PM_{2.5}$, indicating that the relative risk for emergency hospital admissions for respiratory disease increases with increased fine particulate matter exposure.

AQS and CMAQ Results

	Post Mean	Post SD	2.5 th perc	97.5 th perc
AQS	0.0179	0.0088	0.0008	0.0350
CMAQ	0.0225	0.0051	0.0124	0.0325

Table : AQS and CMAQ posterior distribution of the effect of ambient PM_{2.5} on emergency respiratory admissions

- ▶ AQS: posterior mean of $\beta_{PM} = 0.0179$. 95% posterior CI of (0.0008, 0.0350). Corresponds to an increased relative risk (RR) of approximately 1.8% ($e^{0.0179} = 1.018$)
- ▶ CMAQ: posterior mean $\beta_{PM} = 0.0225$. Corresponds to an increased RR of approximately 2.3%

Note: CMAQ results in more precise estimates than AQS, as evidenced by the smaller credible intervals and posterior sd

SHEDS-PM Results

	Post Mean	SD	2.5 th perc	97.5 th perc
Lag1PM _{2.5}	0.0231	0.0049	0.0135	0.0329

Table : SHEDS posterior distribution for the effect of ambient PM_{2.5} and confounding covariates on emergency respiratory admissions

- ▶ Posterior mean of $\alpha_{PM} = 0.0231$ with 95% posterior CI of (0.0135, 0.0329).
- ▶ Corresponds to an increased RR of approximately 2.3% for emergency respiratory hospital admissions
- ▶ An approximate increase of 2.3 admissions per 100, with a 95% posterior credible interval of (1.4, 3.3) for each one standard deviation increase in fine particulate matter (PM_{2.5}) on a given day.

Comparison Across Metrics

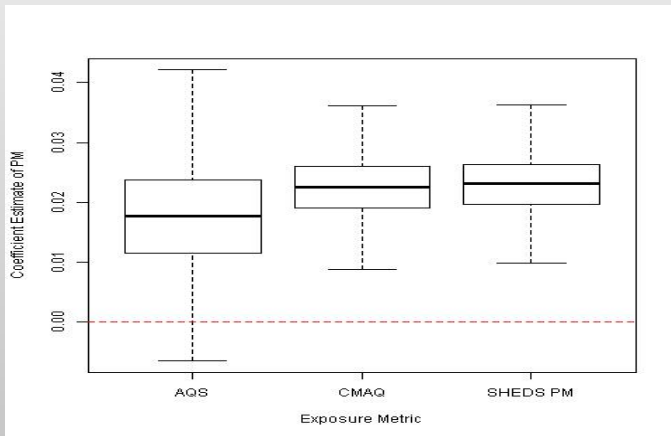


Figure : Posterior distribution of $PM_{2.5}$ coefficients estimates for RESP

SHEDS-PM Results

- ▶ SHEDS results in more precise estimates than AQS, as shown by the smaller CIs, and is comparable to CMAQ.
- ▶ Uncertainty associated with SHEDS coefficient is less than that of AQS, showing a 44% reduction in uncertainty estimates.
- ▶ Uncertainty associated with SHEDS is comparable to that of CMAQ.

Discussion

- ▶ Effect estimates fairly constant across metrics - indicates model is capturing an effect on health due to fine PM rather than due to measurement error in underlying exposure metric.
- ▶ SHEDS provides approximately the same increase in RR associated with emergency respiratory admissions as using CMAQ or AQS as exposure metrics.

However, SHEDS and CMAQ both bring additional information which helps to reduce the uncertainty in our estimated risk by approximately half.

The exposure models SHEDS and CMAQ have errors and sources of uncertainty, and further evaluation of these models is recommended, since this exposure model error could result in a bias in the estimated risk.

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- ▶ However, while CMAQ can provide output at a very high resolution, it is specific to the CMAQ grid cell location, and does not account for population variability introduced by possible movement across grid cells.

SHEDS-PM provides a metric capable of capturing this variability, as it is based on human demographics and activity patterns and time spent in various microenvironments.

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Thank You!

Mannshardt E, Sucic K, Jiao W, Dominci F, Frey HC, Reich B, and Fuentes M. " Comparing exposure metrics for the effects of fine particulate matter on emergency hospital admissions". *Journal of Exposure Science and Environmental Epidemiology* 23, 627-636 (November 2013). doi:10.1038/jes.2013.39

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