Benefits of using enhanced air quality information in human health studies

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Abstract The ability of four (4) enhancements of gridded $PM_{2.5}$ concentrations derived from observations and air quality models to detect the relative risk of long-term exposure to $PM_{2.5}$ are evaluated with a simulation study. The four enhancements include nearest-neighbor (NN or central monitor), ordinary kriging (OK), FUSED (bias-adjusted model output), and direct use of model outputs (CMAQ). The methods are applied to the state of New York. After adjusting for PM estimation bias and range modification, FUSED PM and CMAQ had similar performance and were better than kriged and nearest neighbor PM.

Introduction

The importance of local spatial variability in exposure estimation has recently been emphasized. Photochemical simulation models such as CMAQ provide continuous gridded estimations of pollution levels but despite continual improvement, are often biased, limiting their use 'as is' in health analyses. Garcia et al (2010) showed that a simple technique to fuse observations and model estimates (FUSED PM) creates unbiased gridded maps of PM that respect observations and fill the area devoid of observations with more detail than provided by kriging.

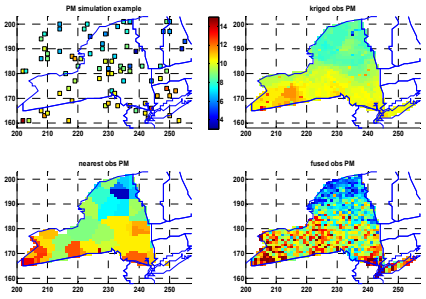

Figure 1. Typical simulation results: top right – observed; top left – kriged; lower left – nearest; lower right - FUSED

In this context, we present a simulation based evaluation of four methods for estimating PM concentrations at unmonitored locations then assess the impact of long-term exposure to PM concentrations on adverse human health outcomes (Miller et al,2007). Long-term exposure is assumed to correspond to the average $PM_{2.5}$ concentrations for the year 2006.

Methods

Simulated 'true' PM_{25} exposure estimates were generated through sequential gaussian simulation (SGS) of 2006 annual mean $PM_{2.5}$ concentrations measured in the US east of the Rocky Mountains (Phase domain, USEPA, 2011). Five hundred equally likely maps were generated. A subset of simulated cells in the vicinity of the state of New York was the designated 'monitoring' network (number of monitors equal 50 for this presentation). An additional subset of 863 cells, consisting of the grid cells in the state of New York, was designated the 'cohort'. The number of individuals per cohort cell was varied between 20 and 100. The enhanced exposure estimates, calculated from the SGS maps include (1) ordinary kriging, (2) fusion (Garcia et al) (FUSED = CMAQ – kriged map of (CMAQ – observations)), (3) nearest neighbor (NN or 'central monitor'), and (4) CMAQ (direct use of model output). Figure 1 shows a typical simulation result.

The link between health affects and air pollution was defined with the Cox proportional hazards model using parameters established by Miller et al (2007) as follows:

$$\gamma = \frac{1}{\lambda_o \exp\left[\beta\,(PM - \overline{PM})\right]} \qquad (1)$$

γ = expected survival time (years) of population members
PM = exposure at a particular location (annual average PM concentration)
$\overline{PM}$ = mean regional exposure
λ_0 = baseline incidence rate (0.032), β = relative risk (0.0215)

Survival times of individuals, denoted $\hat{\gamma}$, are exponentially distributed with mean γ.

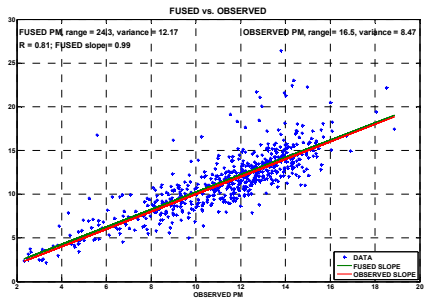

Figure 2. PM FUSED vs. observed: range of FUSED exceeds the observed range

Expected survival times, γ, were calculated from PM values using equation (1). PM values included 'True' and enhanced (using the four methods listed above). Individual survival times, $\hat{\gamma}$, were generated as exponential random numbers given the expected values from equation (1). Finally, partial maximum likelihood regression was used to estimate relative risk (β values) from PM and $\hat{\gamma}$. The estimated β values were compared with the known value of 0.0215.

Results and Discussion

Preliminary results indicated that in terms of bias and root mean squared error, the performance of the four enhanced techniques followed the order OK > (FUSED, nearest neighbor) > CMAQ (OK is best) (Table 1; notice that 'TRUE' PM values (row 1), do not lead to perfect **β** estimates because individual survival times ($\hat{\gamma}$) are exponentially distributed random numbers. Estimation of expected survival times (γ) from 'TRUE' PM values does lead to perfect **β** estimates).

Table 1. Performance of enhanced methods in estimating relative risk (β)

	relative absolute bias (individuals/location)			relative root mean squared error (individuals/location)		
method	**20**	**50**	**100**	**20**	**50**	**100**
TRUE	**0.162**	**0.104**	**0.072**	**0.203**	**0.128**	**0.091**
FUSED	**0.469**	**0.462**	**0.465**	**0.492**	**0.473**	**0.471**
OK	**0.304**	**0.229**	**0.186**	**0.388**	**0.294**	**0.240**
NN	**0.458**	**0.442**	**0.442**	**0.515**	**0.477**	**0.468**
CMAQ	**0.483**	**0.476**	**0.479**	**0.503**	**0.486**	**0.485**

The poor performance of FUSED and CMAQ relative to kriging can be explained by modifications that enhanced techniques impose on the relationship between observed PM and surrogate PM values ($\widehat{PM}$). For example, fused PM is unbiased but has a wider range than true PM (Figure 2); the wider range results in a biased **β** estimate (Figure 3). The bias can be eliminated by dividing the initial **β** estimate by the reliability ratio (Fuller, 1987):

$$\beta\text{ (adjusted)} = \beta\text{ (initial)} / \text{reliability ratio} = \beta\text{ (intial)} / \left(\frac{\sigma^2_{PM}}{\sigma^2_{\widehat{PM}}}\right) \qquad (2)$$

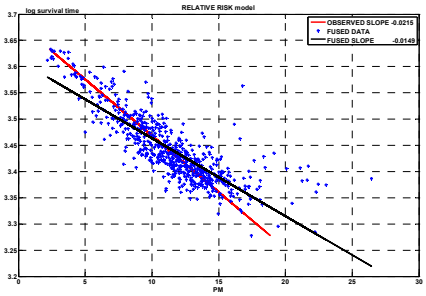

Figure 3. Survival time vs. FUSED PM: to match PM, survival times are rotated counter-clockwise, decreasing the slope (β)

Kriged PM, which is a smoothing of the original PM values, has a reduced range relative to the original PM. Bias caused by the reduced range can be eliminated by multiplying the initial **β** estimate by the slope of PM (true) vs. $\widehat{PM}$(surrogate PM values).

After applying the reliability ratio and the PM/ $\widehat{PM}$ slope to **β,** the performance of the four 'enhanced' PM methods followed the order CMAQ > FUSED ≫ KRIGING ≫ NN (CMAQ best) (Table 2). Figure 4 shows relative root mean squared error for each method as a function of the number of individuals per cohort location.

Table 2. Application of reliability ratio and slope adjustment: performance of enhanced methods (50 monitors)

	relative absolute bias (individuals/ location)			relative root mean squared error (individuals/ location)		
method	**20**	**50**	**100**	**20**	**50**	**100**
TRUE	**0.162**	**0.104**	**0.072**	**0.203**	**0.128**	**0.091**
FUSED	**0.273**	**0.177**	**0.151**	**0.311**	**0.228**	**0.194**
OK	**0.641**	**0.221**	**0.186**	**0.368**	**0.280**	**0.235**
NN	**0.461**	**0.290**	**0.252**	**0.496**	**0.385**	**0.334**
CMAQ	**0.287**	**0.169**	**0.145**	**0.294**	**0.215**	**0.184**

Summary

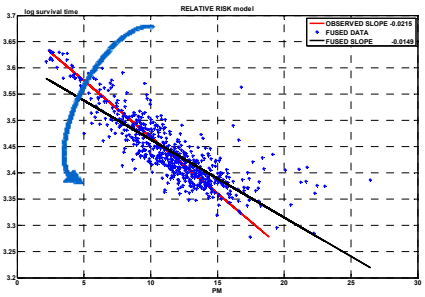

Figure 4. Survival time vs. FUSED PM: to match PM, survival times are rotated counter-clockwise, decreasing the slope (β)

PM estimation bias does not play a role in relative risk estimation, but bias in the variance does, explaining why CMAQ and FUSED maps, though unbiased, perform poorly in relative risk estimation unless adjusted. FUSED map techniques are designed to reduce CMAQ PM bias but could be designed to also reproduce PM variance.

Disclaimer

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Question and Answer

Haluk Ozkaynak: How does bias correction methodology influence the confidence interval estimates of the alternative relative risk (β) estimates?

P. Steven Porter: We did not compute β confidence intervals. Methods with smaller mean squared errors should also have smaller confidence intervals.