



An Empirical Assessment of Exposure Measurement Error and Effect Attenuation in Bi-Pollutant Epidemiologic Models

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Dionisio KL, Baxter LK, Chang HH. An Empirical Assessment of Exposure Measurement Error and Effect Attenuation in Bi-pollutant Epidemiologic Models. Environ Health Perspect; <http://dx.doi.org/10.1289/ehp.1307772>.

Background

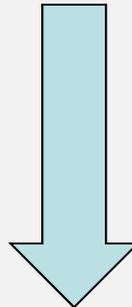
- Exposed to a complex mixture of pollutants
- Multipollutant models can be used to understand the health effects of exposure to mixtures
- Exposures typically estimated using ambient monitoring data but these may not adequately capture
 - spatial and temporal coverage
 - exposures in different microenvironments
 - infiltration

Background

- Differing degrees of exposure error across pollutants
- Previous focus on quantifying and accounting for exposure error in single-pollutant models
- Examine exposure errors for multiple pollutants and provide insights on the potential for bias and attenuation of effect estimates in single and bi-pollutant epidemiological models

Objectives

Quantify the relationships among multiple pollutants and their associated exposure errors across exposure metrics



Use empirical values to determine the potential attenuation of coefficients in bi-pollutant epidemiologic models

Methods

1. Compare exposure metrics within- and across-pollutants
2. Compare exposure errors within- and across-pollutants
3. Using results from 1) and 2) calculate attenuation factors for single and bi-pollutant model coefficients

Methods: Exposure Metrics

- Estimated daily exposures to ambient air pollution for 193 ZIP codes in the Atlanta, GA (1999-2002)
 1. **CS: Central-site measurements**
 - From SEARCH, ASACA, and U.S. EPA's AQS monitoring networks
 - 24-hr average concentrations (PM_{2.5}, EC, and SO₄)
 - Hourly concentrations aggregated to 24-hr averages (CO, NO_x) or 8-hr maximum (O₃)
 2. **AQ: Air quality model estimates**
 - Combines local-and regional-scale model results
 3. **PE: Stochastic population exposure model estimates**
 - Stochastic Human Exposure and Dose Simulation Air Toxics (SHEDS-AT) model

Dionisio et al. (2013). "Development and evaluation of alternative approaches for exposure assessment of multiple air pollutants in Atlanta, Georgia." J Expos Sci Environ Epidemiol 23(6): 581-592.

Methods: Exposure Error

- Exposure error, δ , is calculated as the difference between two exposure metrics:
 - $\delta_{\text{spatial}} = \text{AQ} - \text{CS}$; exposure error due to a lack of spatial refinement
 - $\delta_{\text{population}} = \text{PE} - \text{AQ}$; exposure error due to lack of human exposure factors
 - $\delta_{\text{total}} = \text{PE} - \text{CS}$; exposure error due to lack of both spatial variability and human exposure factors

Methods: Attenuation Factors for Single Pollutant Models

$$\lambda = \frac{1}{1 + \frac{\text{var}(\delta)}{\text{var}(x_{\text{fine}})}}$$

$$\beta_{\text{observed}} = \lambda * \beta_{\text{true}}$$

λ = attenuation factor

δ = exposure error

$\text{var}(\delta)$ = the variance across days of δ

x_{fine} = the exposure metric with the greater degree of refinement (i.e., increased spatial resolution, or inclusion of weighting by population factors)

$\text{var}(x_{\text{fine}})$ = the variance across days of x_{fine}

β = model coefficients

$\lambda = 1$ indicates no attenuation

$\lambda = 0$ indicates null results

Methods: Attenuation Factors for Bi-pollutant Models

$$\lambda_{x_1} = \mathbf{S}(\mathbf{S} + \mathbf{V})^{-1}$$

$$\beta_{observed,x_1} = \lambda_{x_1} \times \beta_{true,x_1}$$

λ_{x_1} = attenuation factor for pollutant x_1 in a classical error, bi-pollutant model, assuming pollutant x_2 has no effect ($\beta_{x_2} = 0$)

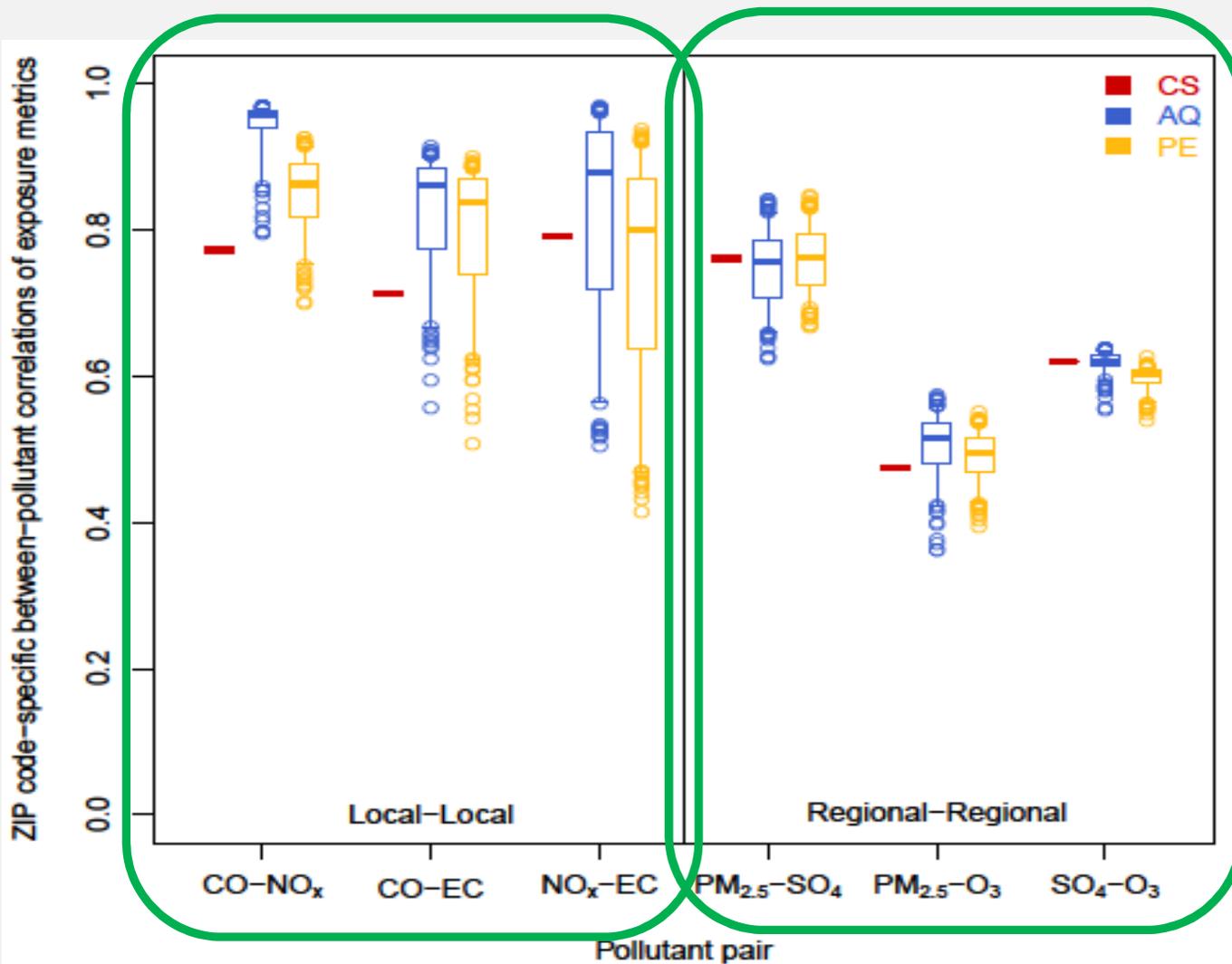
\mathbf{S} = covariance of the more refined exposure metric for x_1 and x_2

\mathbf{V} = covariance of the exposure errors for x_1 and x_2

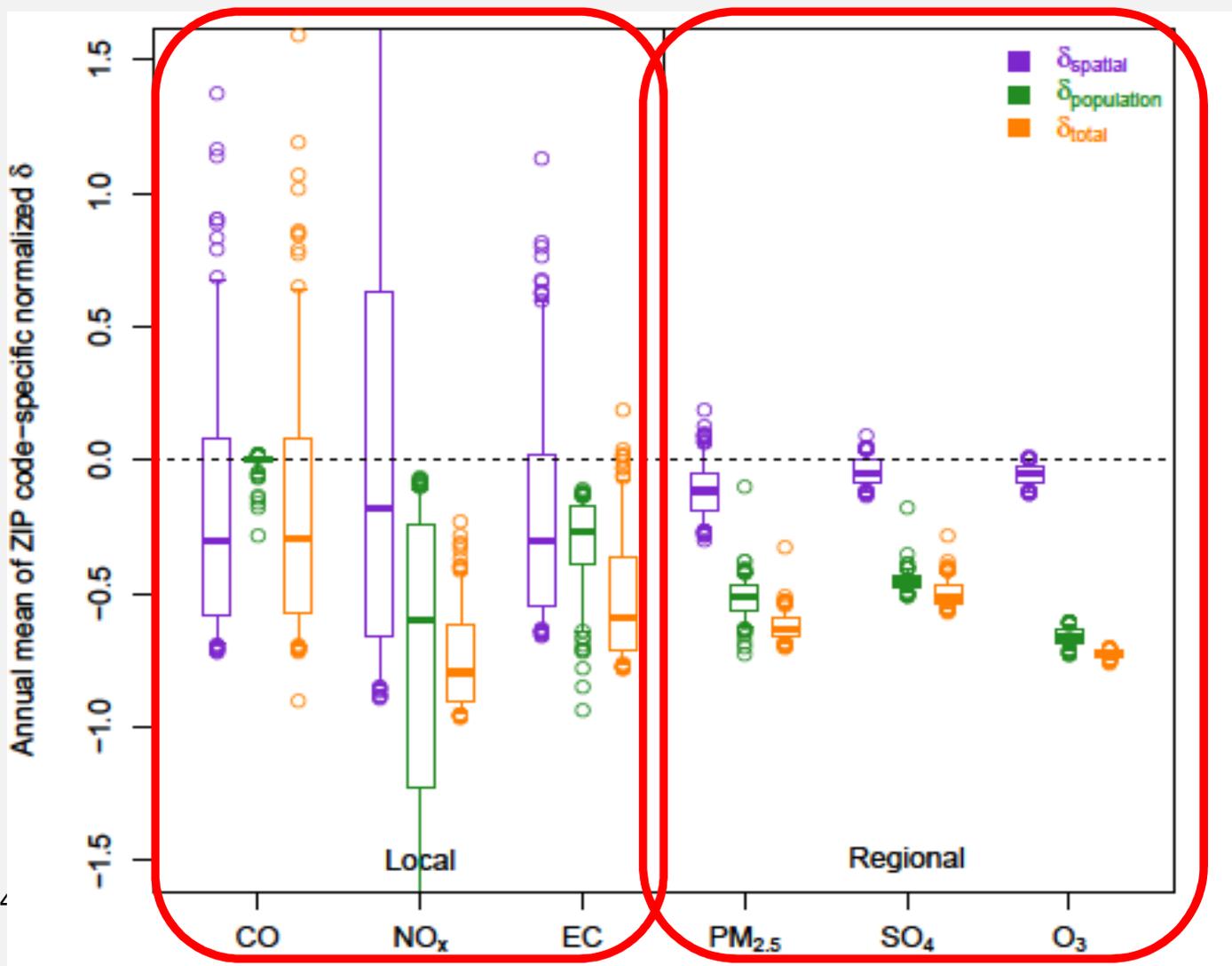
Modified from Zeger et al. (2000). "Exposure measurement error in time-series studies of air pollution: concepts and consequences." Environmental Health Perspectives 108(5): 419-426.

Results: Relationships between multiple pollutants and their associated exposure errors

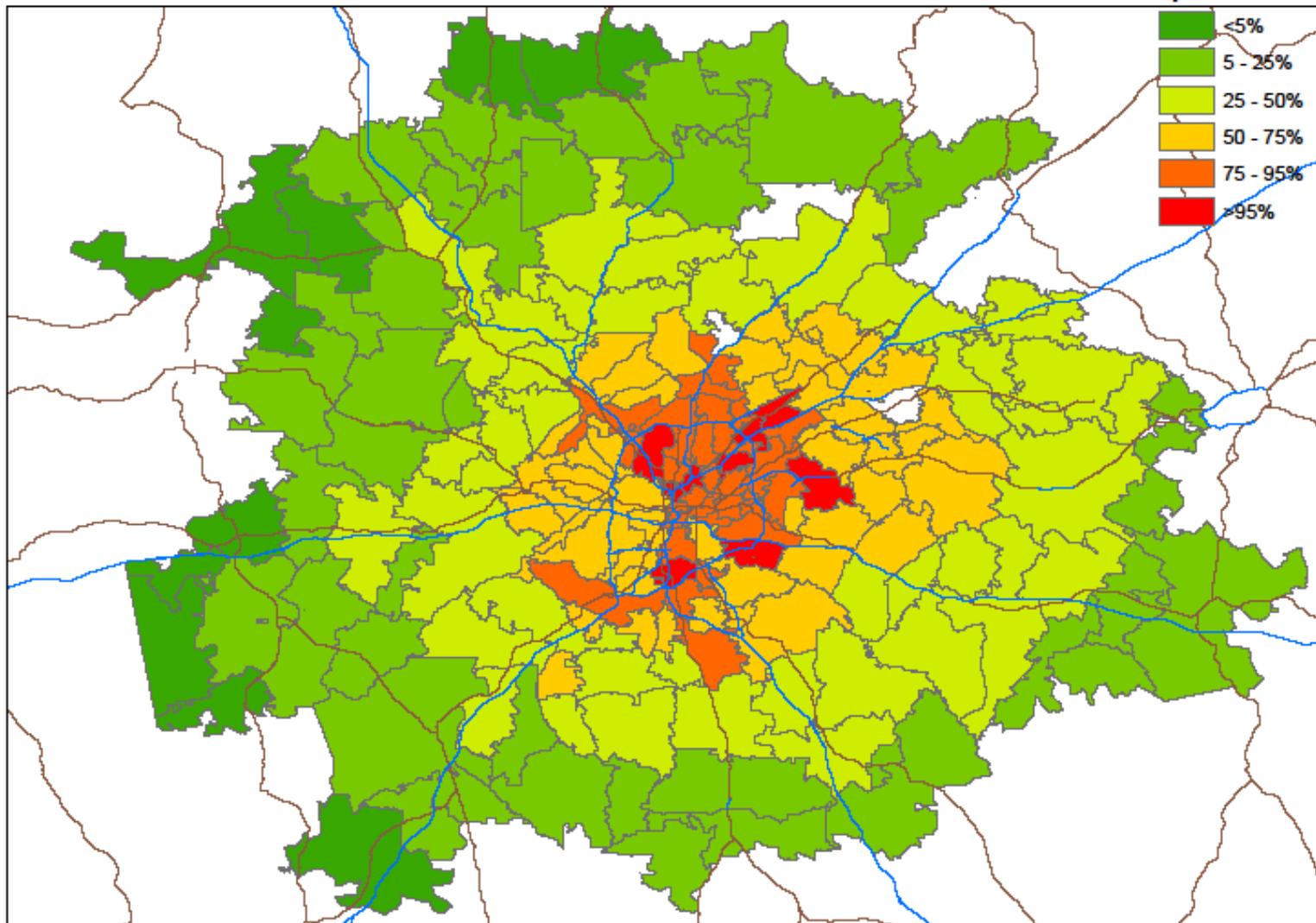
Distributions of pearson correlations between daily exposure metrics (n= 193 zip codes)



Normalized (divided by annual average CS measurement) ZIP code-specific exposure error estimates



Map of δ_{spatial} for NO_x in Atlanta, GA

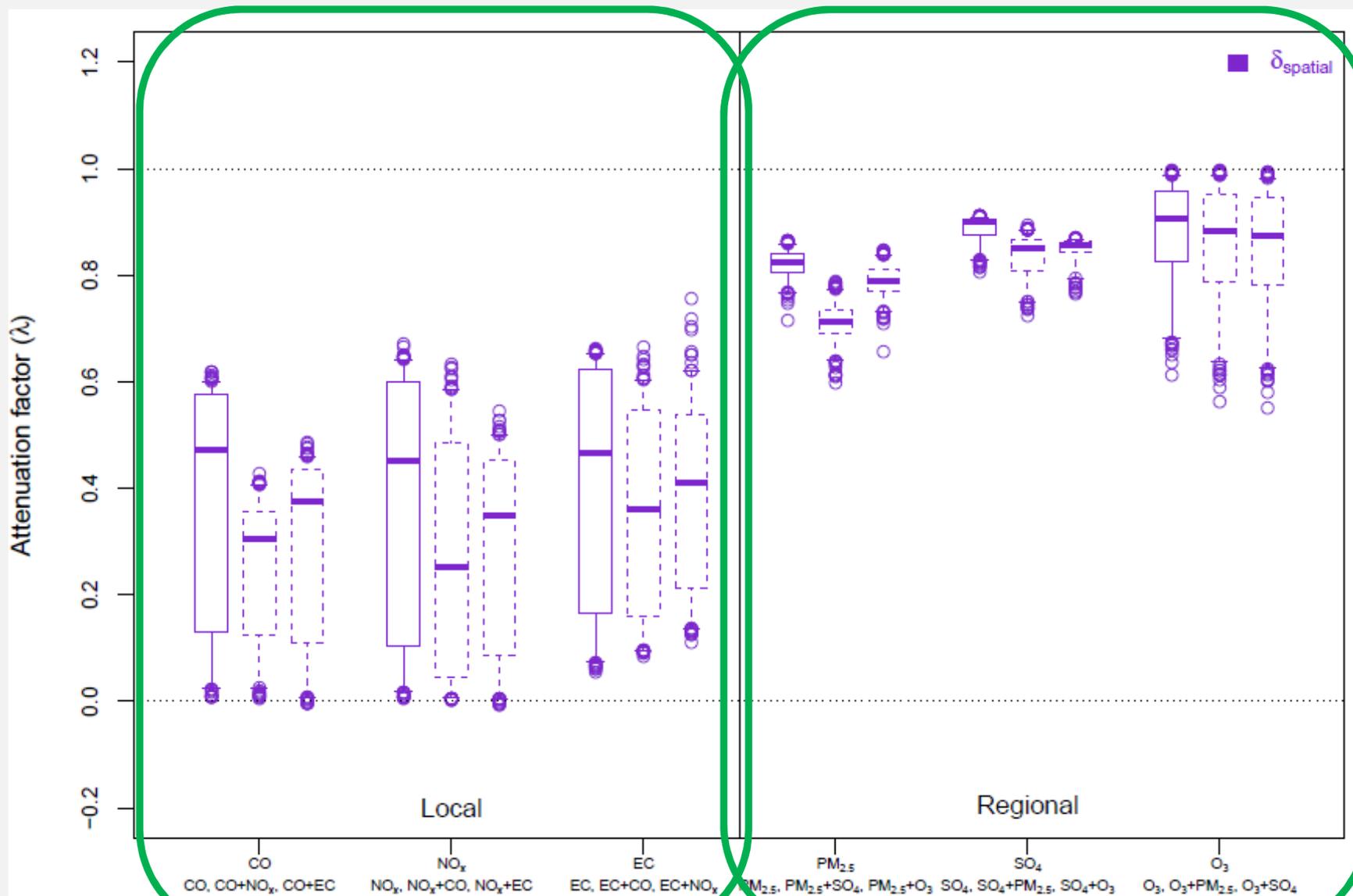


Colored regions represent ZIP codes in the study area, blue and brown lines indicate major roads.

Legend is grouped by percentile, where 5% = -0.85; 25% = -0.66; 50% = -0.18; 75% = 0.63; and 95% = 1.73.

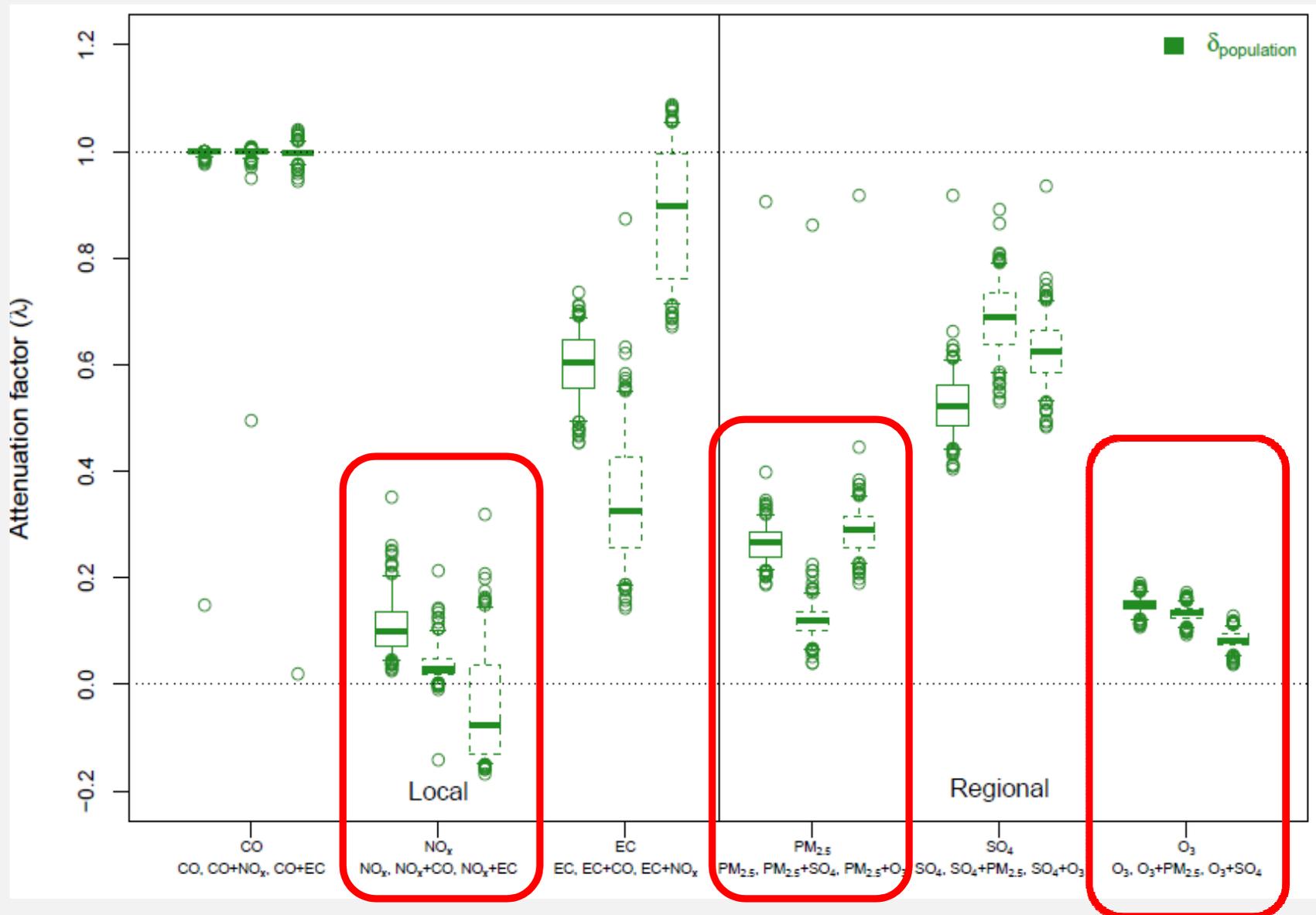
Results: Attenuation Factors

Attenuation factors due to δ_{spatial}



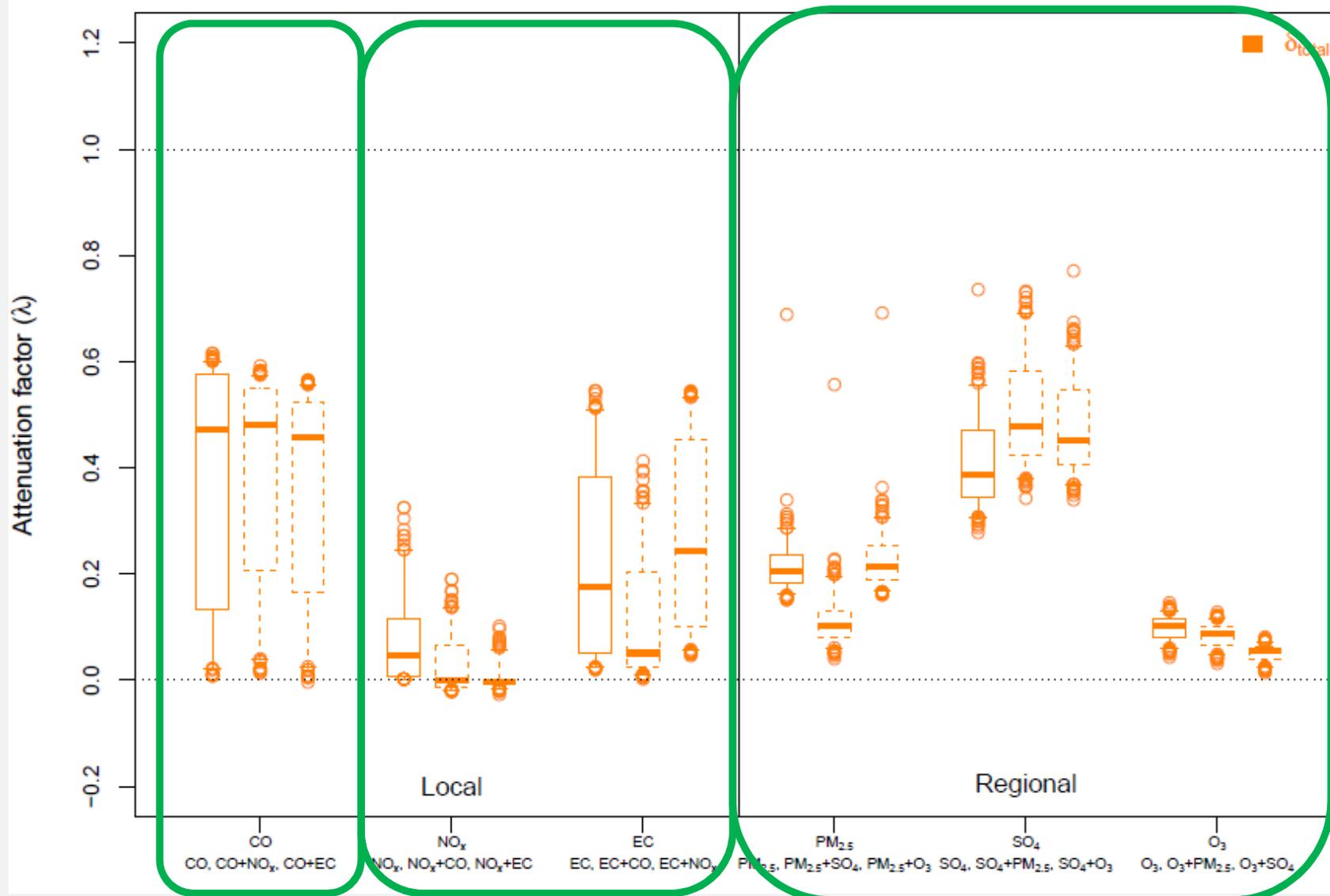
Solid boxplots = single pollutant models; Dashed boxplots = bi-pollutant models

Attenuation factors due to $\delta_{\text{population}}$



Solid boxplots = single pollutant models; Dashed boxplots = bi-pollutant models

Attenuation factors due to δ_{total}



Solid boxplots = single pollutant models; Dashed boxplots = bi-pollutant models

Summary and Conclusions

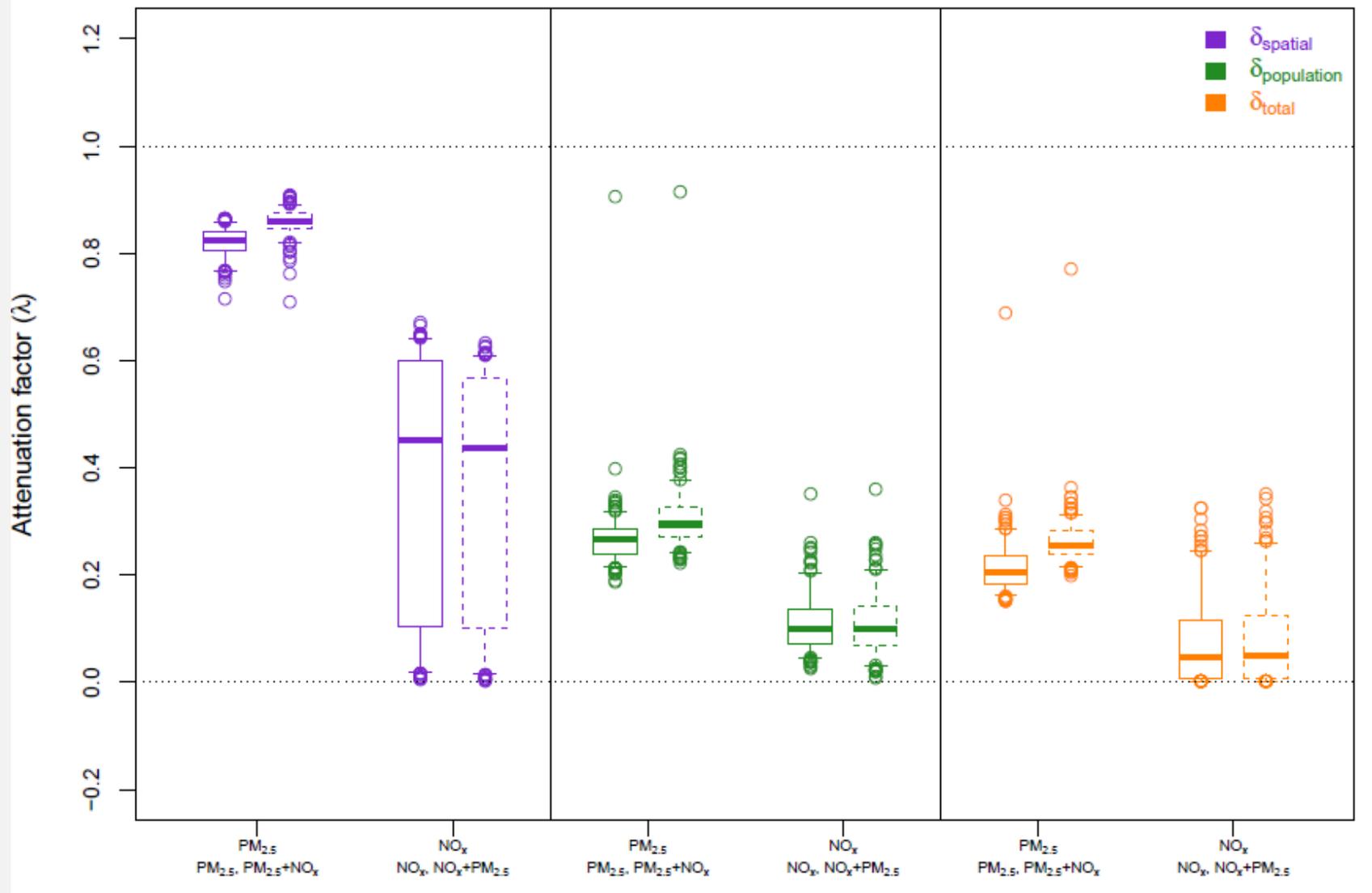
- Attenuation of coefficients for bi-pollutant models, particularly for local pollutants (CO, NO_x, EC)
- Spatially varying attenuation due to spatial variability (i.e. differences between zip codes)
- More research are exploring multipollutant approaches
 - Effects on model coefficients will depend on relationships between pollutants and their errors
- Next step: simulation study including the empirically determined covariance structures to quantify the effect on bi-pollutant model coefficients

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- Emory University: Stefanie Sarnat, Jeremy Sarnat
- Georgia Tech: Jim Mulholland

Disclaimer: Although this work was reviewed by EPA and approved for publication, it may not necessarily reflect official Agency policy.

Attenuation Factors for a local-regional pollutant pair example



Results: Parameters impacting attenuation and bias in a bivariate pollutant model^a

x_1	x_2	AQ		PE	$\delta_{spatial}$			$\delta_{population}$			δ_{total}		
		$Corr(x_1, x_2)$	$Corr(x_1, x_2)$		$Var(\delta_1)^b$	$Var(\delta_2)^b$	$Corr(\delta_1, \delta_2)$	$Var(\delta_1)^b$	$Var(\delta_2)^b$	$Corr(\delta_1, \delta_2)$	$Var(\delta_1)^b$	$Var(\delta_2)^b$	$Corr(\delta_1, \delta_2)$
<i>Local-Local pollutant pairs</i>													
CO	NO _x	0.96	0.86		0.25	0.83	0.73	0.00	0.32	-0.13	0.25	0.80	0.35
CO	EC	0.86	0.84		0.25	0.30	0.65	0.00	0.05	-0.19	0.25	0.33	0.52
NO _x	EC	0.88	0.80		0.83	0.30	0.76	0.32	0.05	0.85	0.80	0.33	0.72
<i>Regional-Regional pollutant pairs</i>													
PM _{2.5}	SO ₂	0.76	0.76		0.04	0.05	0.21	0.09	0.10	0.77	0.12	0.16	0.70
PM _{2.5}	O ₃	0.52	0.49		0.04	0.02	0.03	0.09	0.11	0.52	0.12	0.16	0.41
SO ₂	O ₃	0.62	0.60		0.05	0.02	0.11	0.10	0.11	0.62	0.16	0.16	0.57

^a All values presented are median across all ZIP codes; ^b $Var(\delta)$ represents variance of normalized exposure error

* builds upon the hypothetical simulation presented in Zeger et al. (2000)