Comparing Remote Sensing, Atmospheric Chemistry, and Ground-based Estimates of Fine Particulate Matter on Survival

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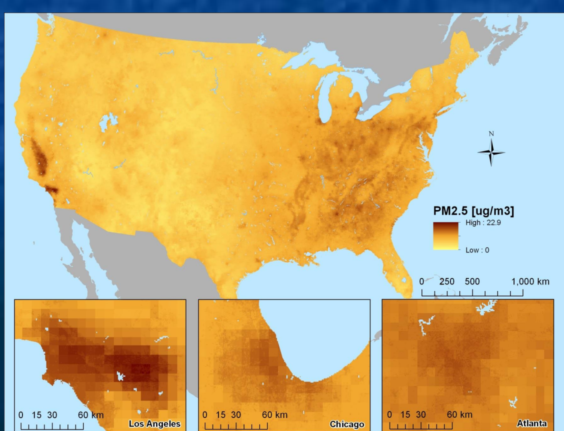
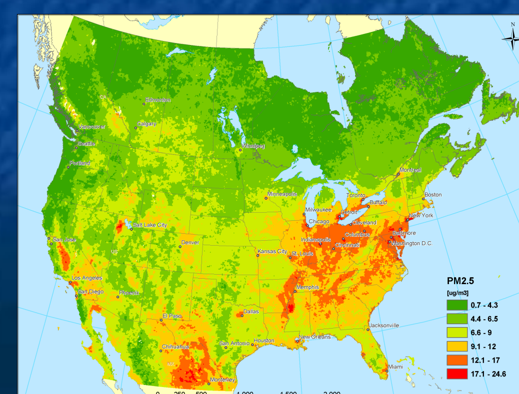


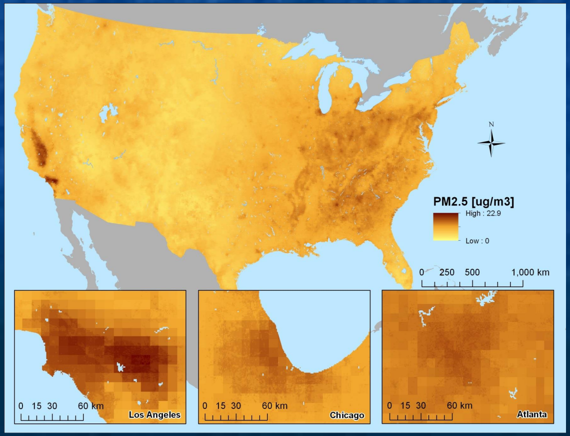


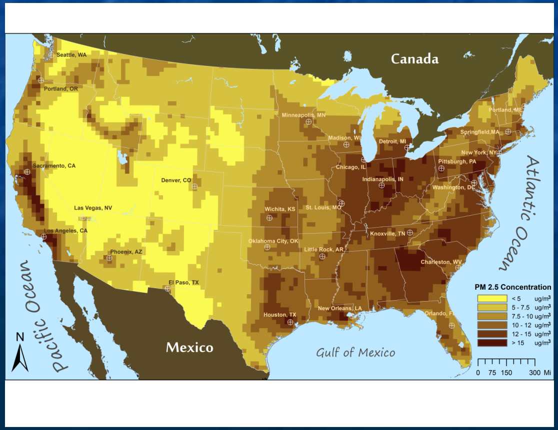
Exposure Assignments in Chronic Cohort Studies

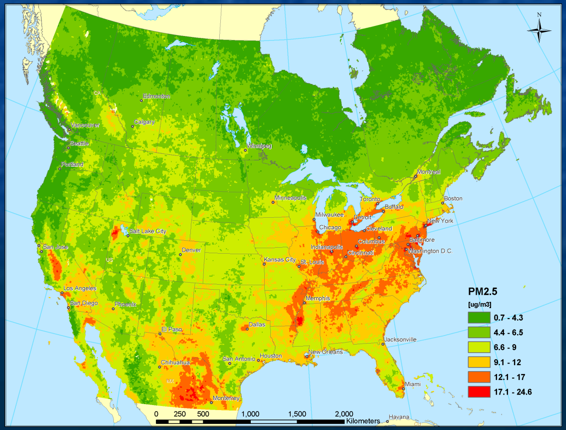
- Growing availability of Atmospheric Chemistry, Remote Sensing, and Hybrid models important innovations for the study of long-term health effects
- Few studies have compared the different model types in health effects assessment
- Raises questions about validity and comparability of the results

Research Objective

- To compare the effects of seven different $PM_{2.5}$ exposure estimates on survival in the United States based on the American Cancer Society Cohort Cancer Prevention II Study







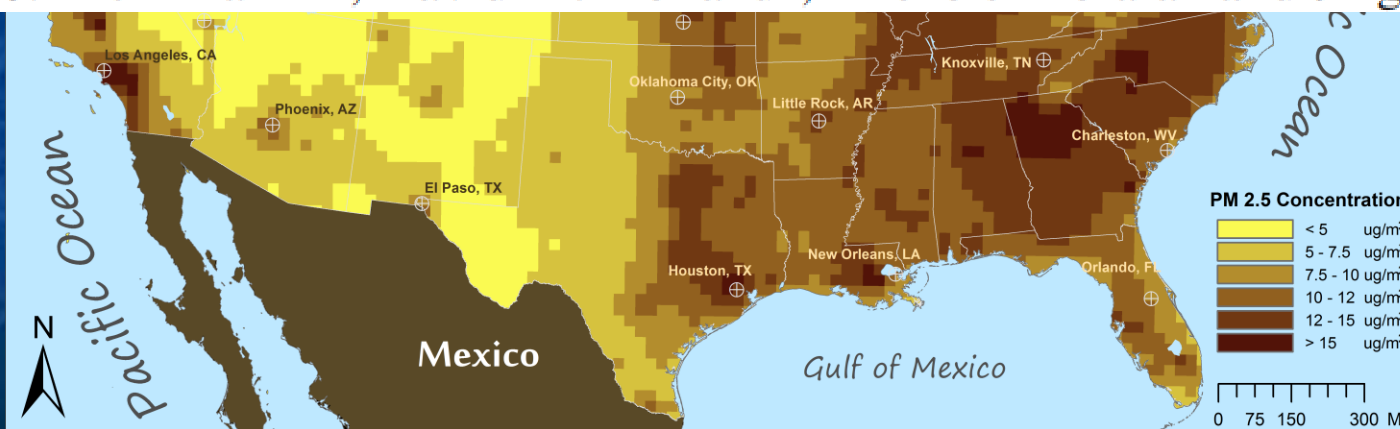
Exposure Models Evaluated

- U.S. EPA Hierarchical Bayesian model (Atmospheric Chem model fused to ground ~ 36 km resolution)
- Remote sensing (RS) model (van Donkalaar et al. 2010, 2013 ~ 9.8 km resolution – 3 models)
- Bayesian Maximum Entropy (BME) Space-time kriging models (~ 9.8 km resolution)
- Hybrid models (Land Use Regression BME ~ 100 m resolution)

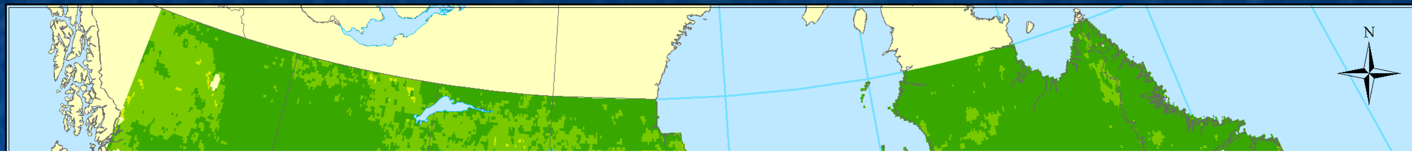
U.S. EPA Hierarchical Bayesian Model (CMAQ fused to Ground)

Combining numerical model output and particulate data using Bayesian space–time modeling

Nancy J. McMillan[1*,†], David M. Holland[2], Michele Morara[1] and Jingyu Feng[1]



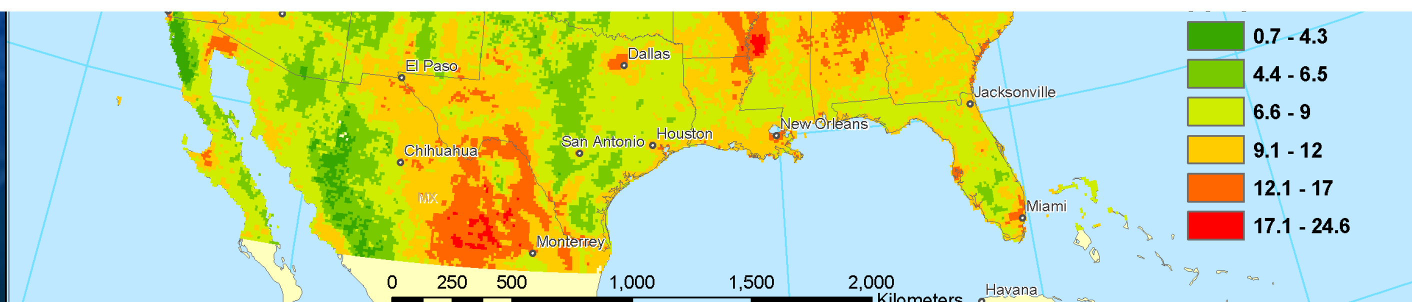
$PM_{2.5}$ Predictions from Integrated Remote Sensing-Meteorology Model



Exposure assessment for estimation of the global burden of disease attributable to outdoor air pollution

Michael Brauer[1,*], Markus Amann[2], Rick T. Burnett[3], Aaron Cohen[4], Frank Dentener[5], Majid Ezzati[6], Sarah B. Henderson[7], Michal Krzyzanowski[8], Randall V. Martin[9,10], Rita Van Dingenen[5], Aaron van Donkelaar[9], and George D. Thurston[11] on behalf of the Outdoor Air Pollution Expert Working Group of the Global Burden of Disease Project

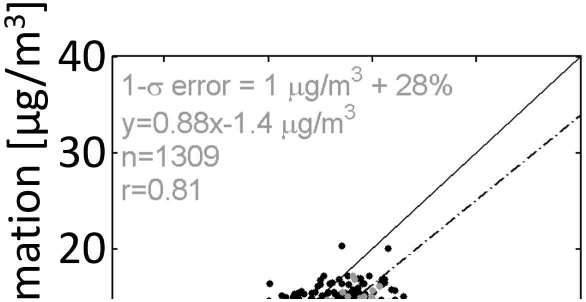
[1]School of Population and Public Health, The University of British Columbia, 2206 East Mall, Vancouver, BC, V6T1Z3 Canada



Source: van Donkelaar et al. 2010

Relate satellite-based retrievals of *aerosol optical depth* (AOD) to *$PM_{2.5}$* using a global chemical transport model

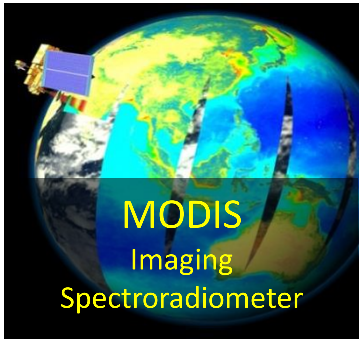
(R.Martin, PI)

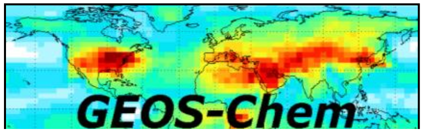


Extend previous work with:

- Optimal Estimation AOD
- CALIOP-adjusted AOD/$PM_{2.5}$

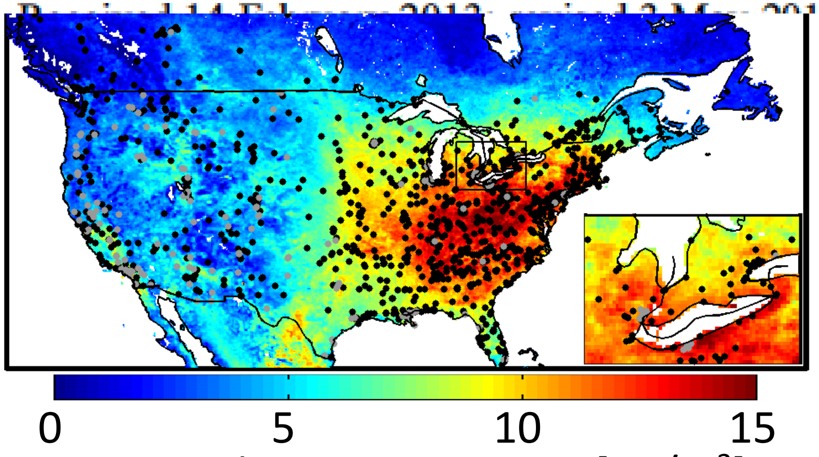
Optimal Estimation allows:





Optimal estimation for global ground-level fine particulate matter concentrations

Aaron van Donkelaar,[1] Randall V. Martin,[1,2] Robert J. D. Spurr,[3] Easan Drury,[4] Lorraine A. Remer,[5] Robert C. Levy,[6,7] and Jun Wang[8]



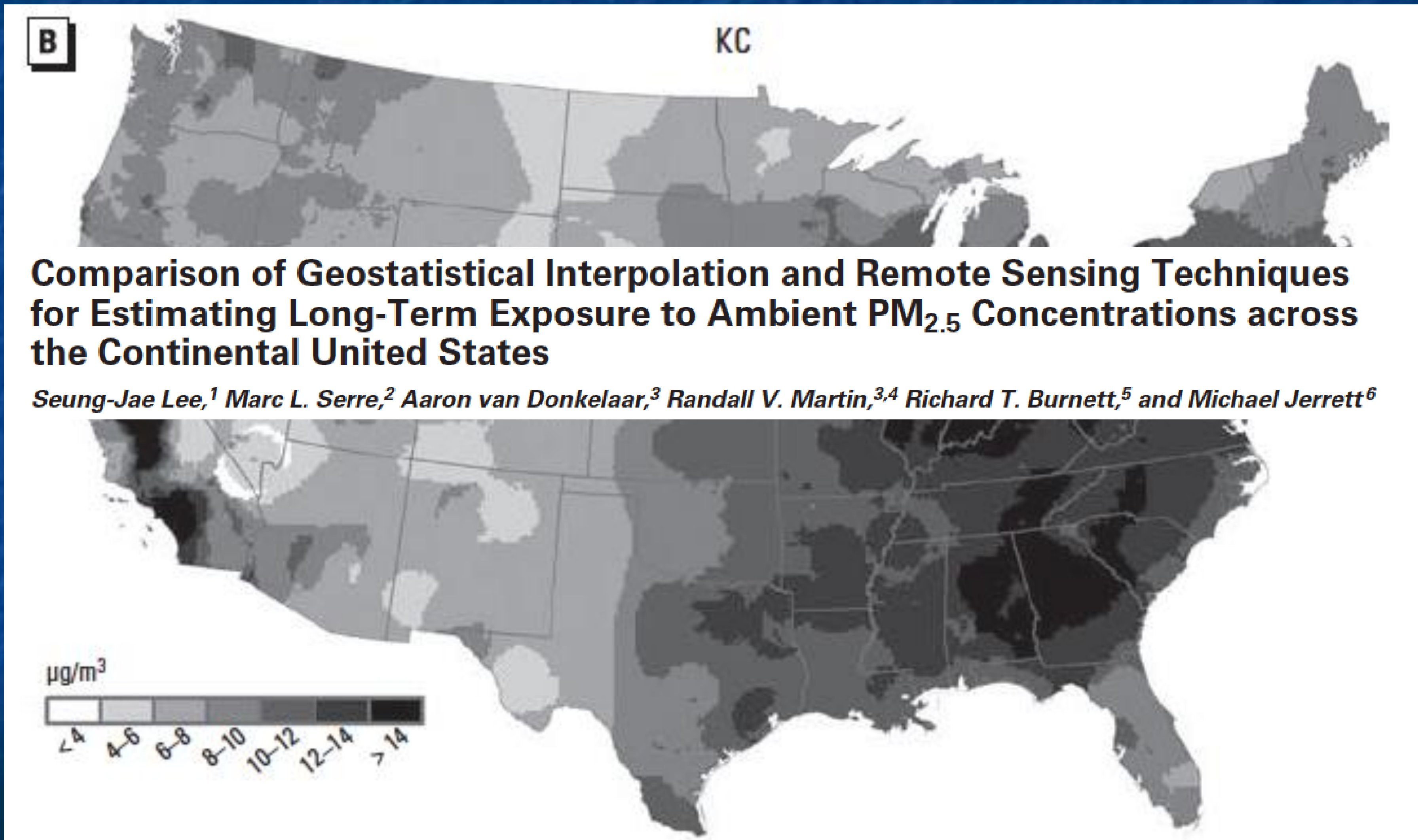
a posteriori AOD — *a priori* AOD — Observed TOA reflectance

$$J(AOD) = \frac{(AOD - AOD_a)^2}{\sigma_a^2} + \frac{\left(\rho - \left[\frac{d\rho_a}{dAOD_a}\right] AOD\right)^2}{\sigma_\varepsilon^2}$$

a priori error — observational error

van Donkelaar et al., submitted

BME Spatiotemporal Exposure Model (Lee et al. 2012)



Comparison of Geostatistical Interpolation and Remote Sensing Techniques for Estimating Long-Term Exposure to Ambient $PM_{2.5}$ Concentrations across the Continental United States

Seung-Jae Lee,[1] Marc L. Serre,[2] Aaron van Donkelaar,[3] Randall V. Martin,[3,4] Richard T. Burnett,[5] and Michael Jerrett[6]

Hybrid Models based on Land Use Regression/Kriging/Remote Sensing

Environmental Science & Technology

Article

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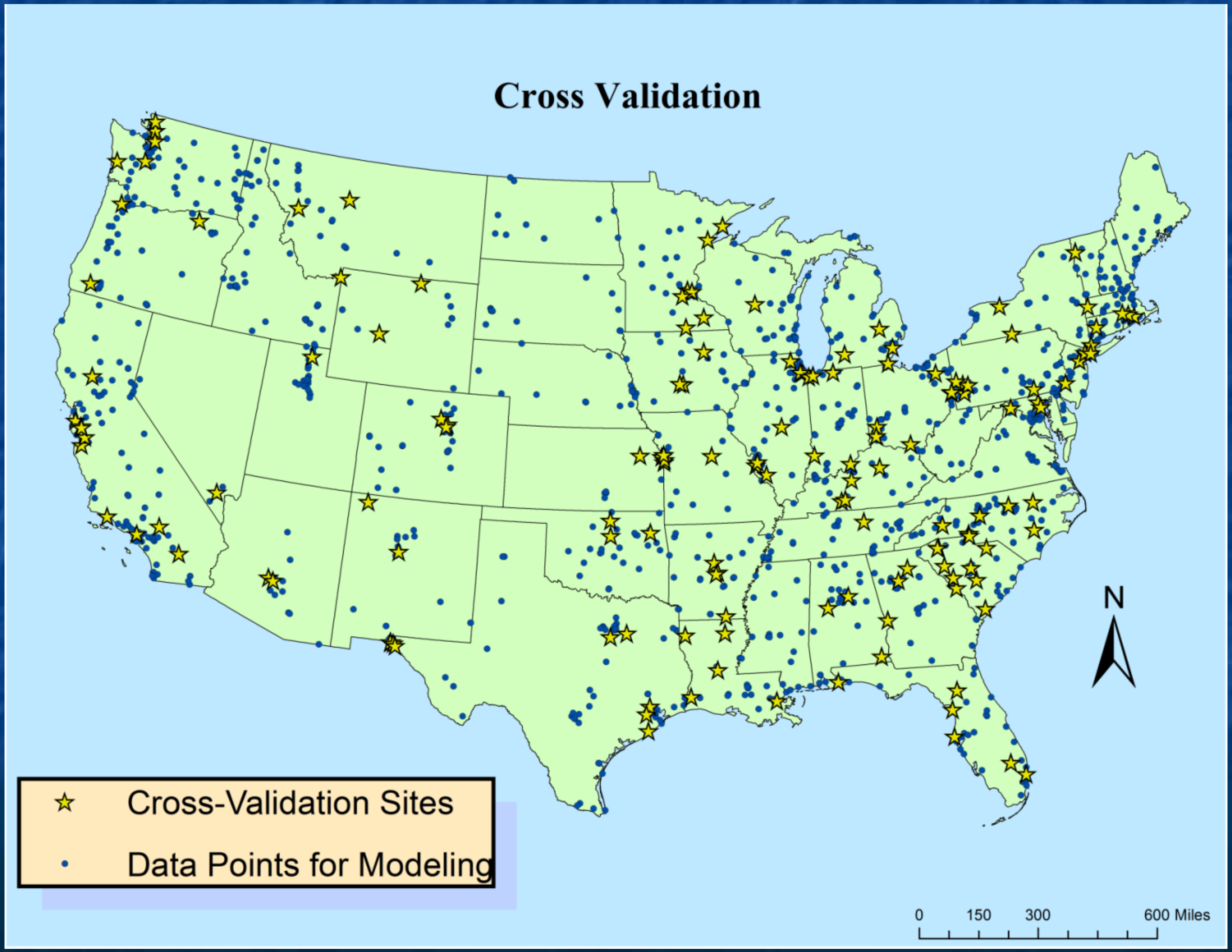
A Hybrid Approach to Estimating National Scale Spatiotemporal Variability of $PM_{2.5}$ in the Contiguous United States

Bernardo S. Beckerman,[*,†] Michael Jerrett,[†] Marc Serre,[‡] Randall V. Martin,[§] Seung-Jae Lee,[‖] Aaron van Donkelaar,[§] Zev Ross,[⊥] Jason Su,[†] and Richard T. Burnett[#]

Objective 1: Developing the $PM_{2.5}$ Model

1. Assemble comprehensive database of all available PM2.5 monitors
2. Process into monthly averages with 50% completeness criteria
3. Derive land use and traffic estimates for all monitors
4. Assign remote sensing model predictions of PM2.5 to all monitors (~ 10 km * 10 km grids)
5. Use V-fold cross-validation deletion-substitution algorithms to select significant variables
6. Select land use regression (LUR) model to represent mean trend using Generalized Estimating Equation
7. Take monthly residuals from model and fit with a Bayesian Maximum Entropy (BME) model
8. Combine estimates from the LUR model with the BME model to estimate exposures
9. Cross-validate against leave out sites
10. Assign exposures to small areas (ACS subjects, census tracts, zip codes)

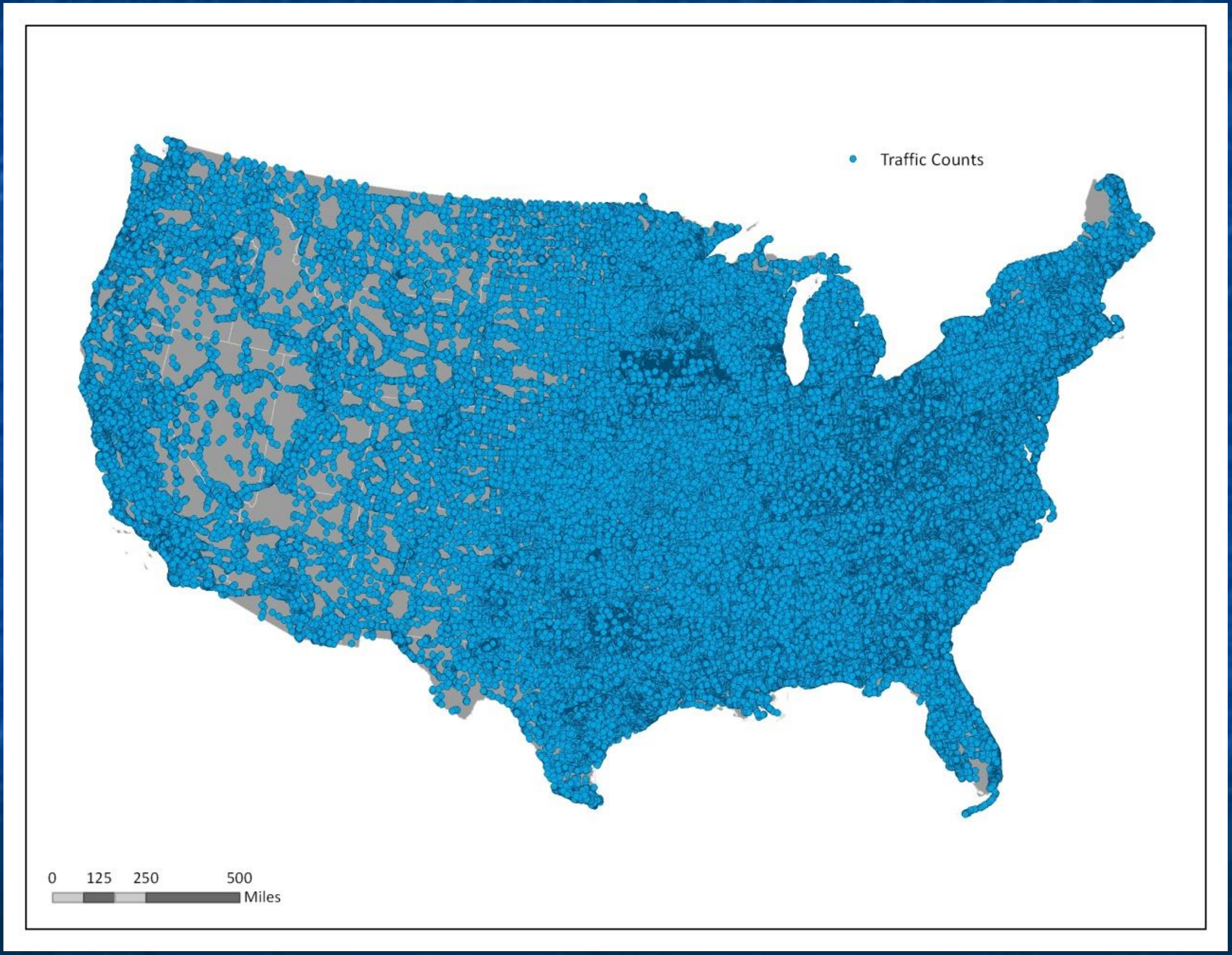
$PM_{2.5}$ Monitoring Locations



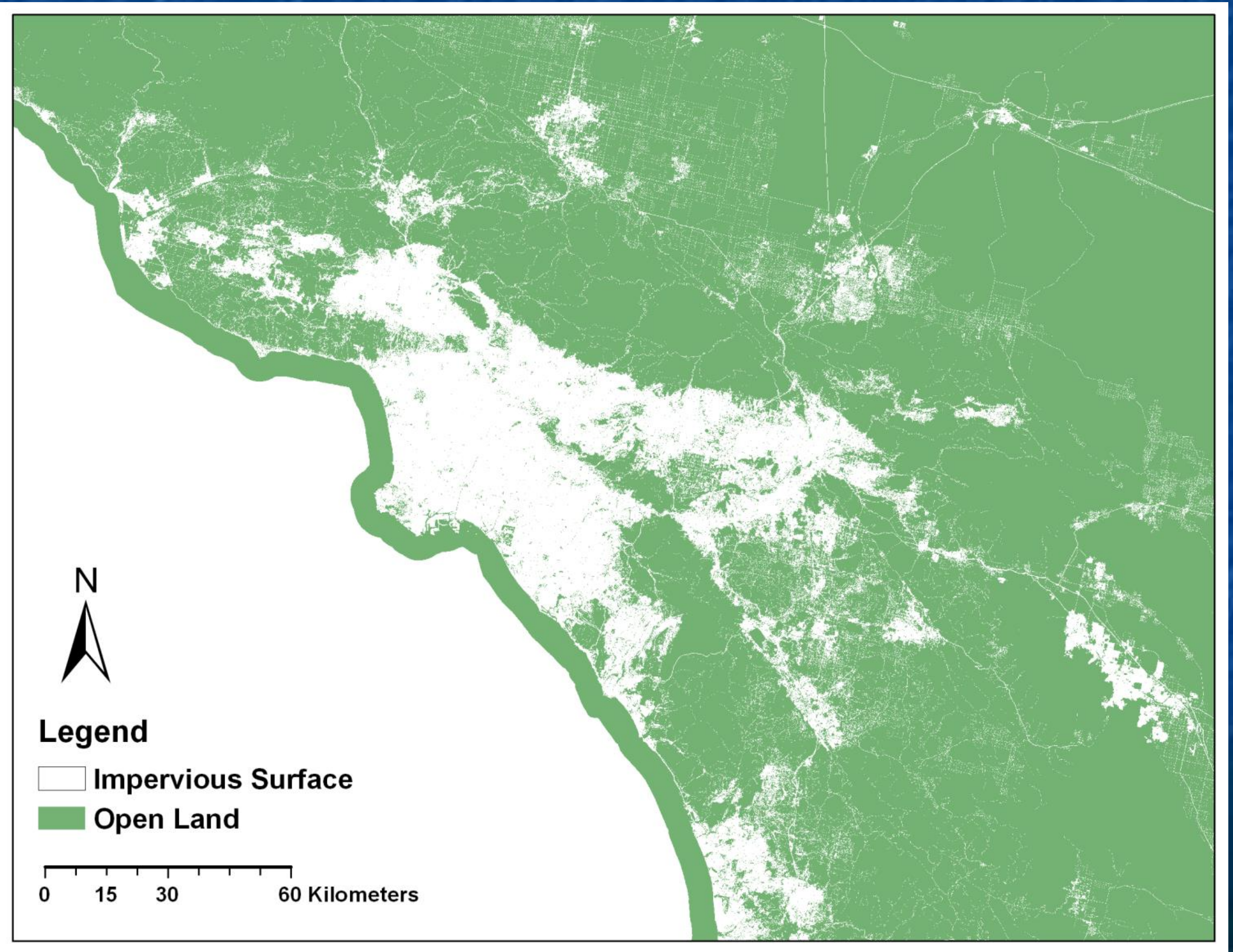
Land Use and Traffic

- Comprehensive database of land use and traffic
- Traffic derived from 40 million count points aligned to the TeleAtlas road network

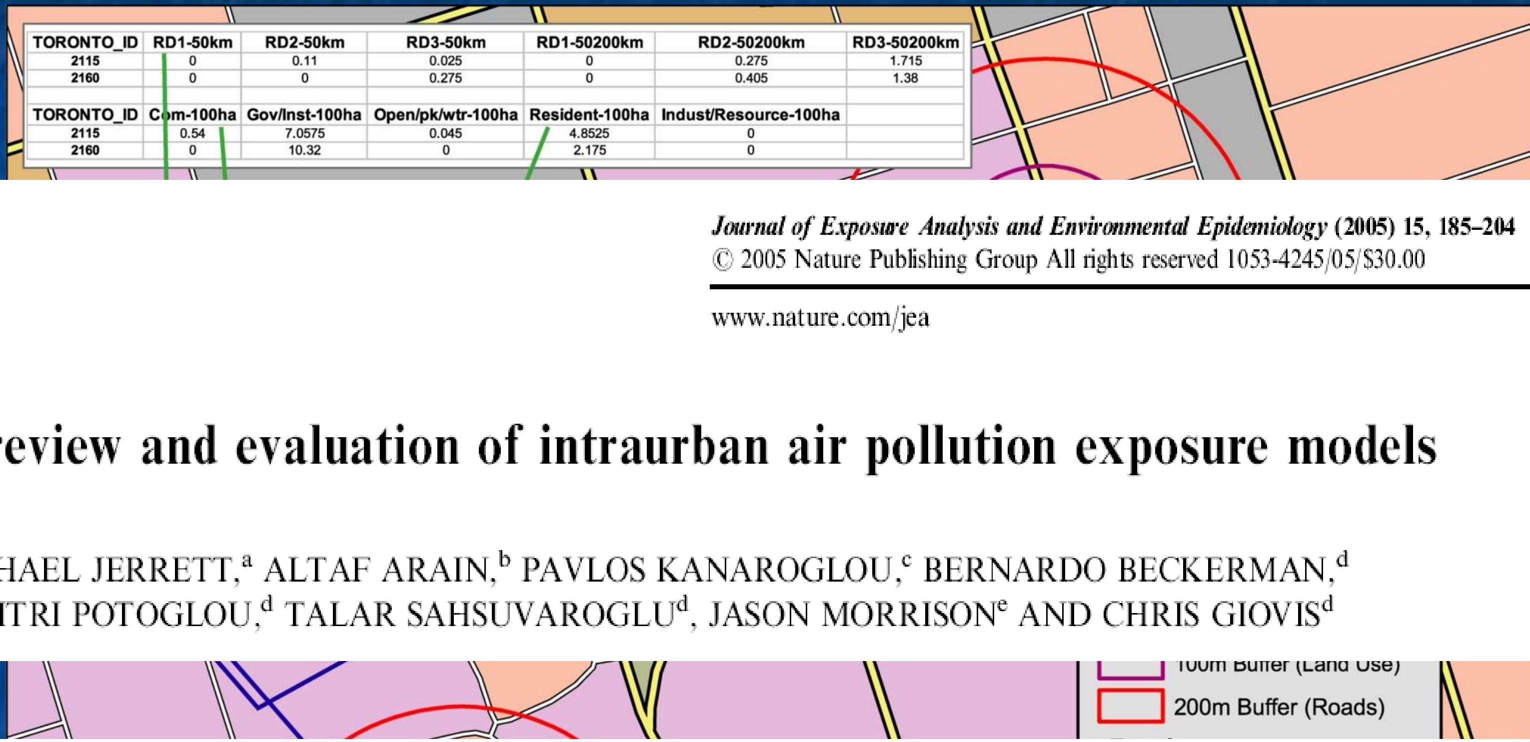
Map of Traffic Count Locations



Open Land Use Los Angeles



Land Use Regression Modeling



TORONTO_ID	RD1-50km	RD2-50km	RD3-50km	RD1-50200km	RD2-50200km	RD3-50200km
2115	0	0.11	0.025	0	0.275	1.715
2160	0	0	0.275	0	0.405	1.38

TORONTO_ID	Com-100ha	Gov/Inst-100ha	Open/pk/wtr-100ha	Resident-100ha	Indust/Resource-100ha
2115	0.54	7.0575	0.045	4.8525	0
2160	0	10.32	0	2.175	0

Journal of Exposure Analysis and Environmental Epidemiology (2005) 15, 185–204

www.nature.com/jea

A review and evaluation of intraurban air pollution exposure models

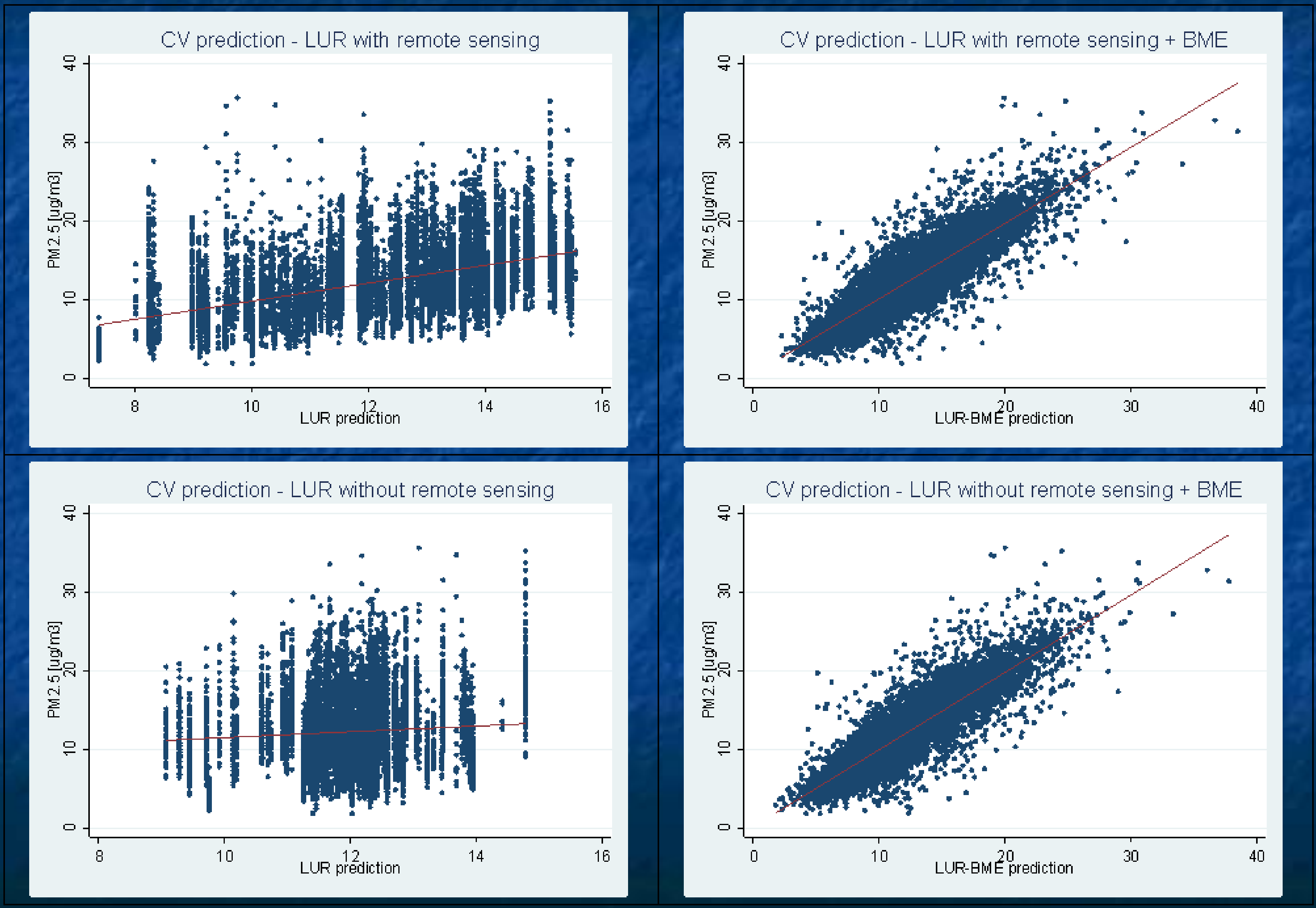
MICHAEL JERRETT,[a] ALTAF ARAIN,[b] PAVLOS KANAROGLOU,[c] BERNARDO BECKERMAN,[d] DIMITRI POTOGLOU,[d] TALAR SAHSUVAROGLU[d], JASON MORRISON[e] AND CHRIS GIOVIS[d]

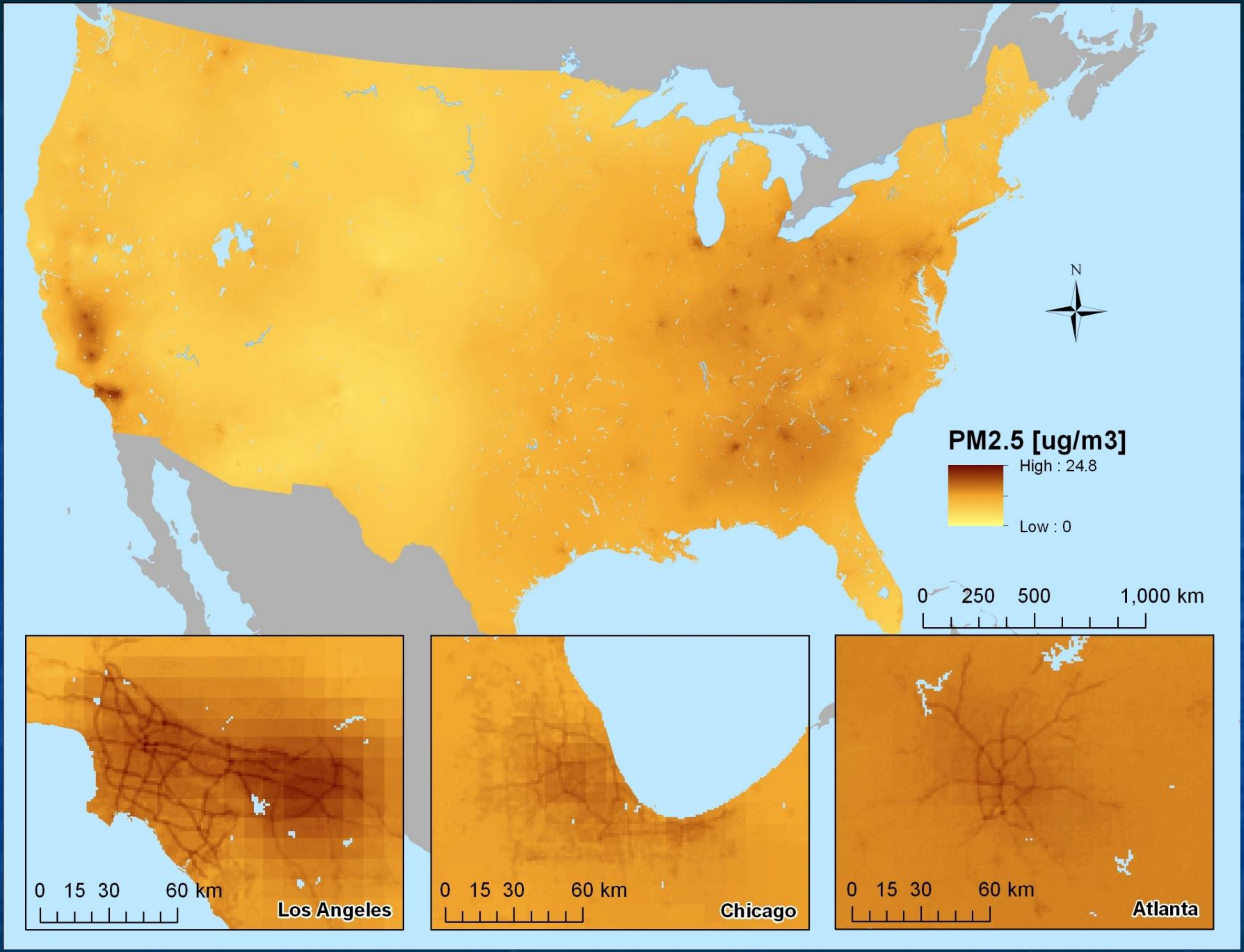
Monitored pollution values are used as the dependent variable in a regression model with proximate traffic, land use, population, and physical geography variables as predictors

Results of the LUR Regression Modeling Using Deletion/Substitution/Addition Selection (after screening 85 variables)

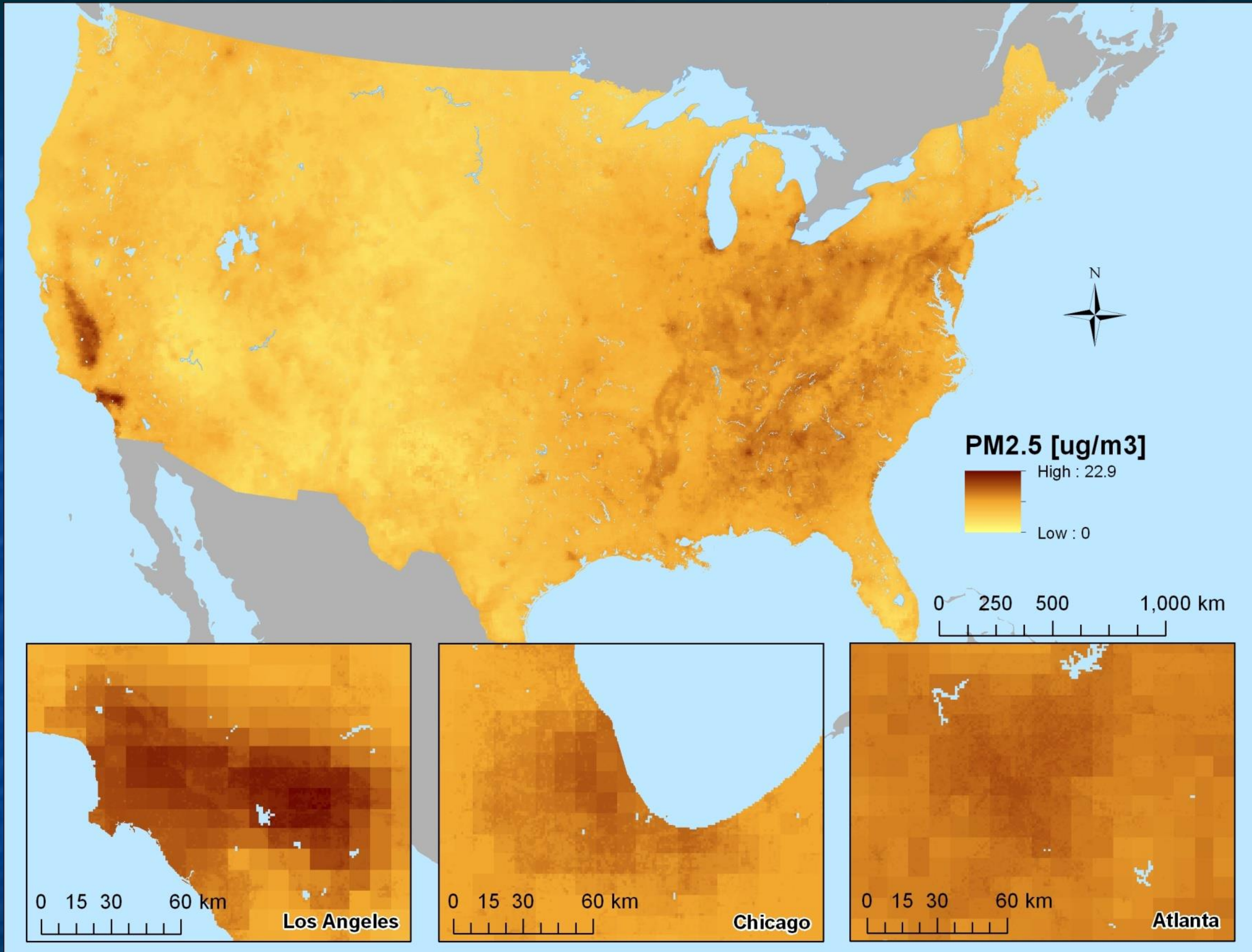
	Modeled PM2.5	Coef.	Robust Std. Err.	z	P>z	[95% Conf	Interval]
USA – without Remote Sensing	Traffic Weights – Vehicle-KM (1000 m)	1.06E-04	1.37E-05	7.760	0.00E+00	7.94E-05	1.33E-04
	Green Space – Acres (100 m)	-4.88E-03	9.90E-04	-4.930	0.00E+00	-6.82E-03	-2.94E-03
	intercept	11.361	0.146	77.610	0.00E+00	11.074	11.648
USA – With Remote Sensing	Remote Sensing PM2.5: squared	0.070	3.00E-03	23.380	0.00E+00	0.064	0.076
	Remote Sensing PM2.5: cubed	-2.45E-03	1.31E-04	-18.700	0.00E+00	-2.70E-03	-2.19E-03
	Developed Land - Acres (200 m)	0.041	0.006	6.650	0.00E+00	0.029	0.053
	intercept	5.923	0.222	26.660	0.00E+00	5.488	6.359

Predictions: R^2 Leave out ~ 80%





$PM_{2.5}$ surface for BME-LUR model without remote sensing averaged over study period



$PM_{2.5}$ surface for BME-LUR model with remote sensing averaged over study period

Comparing Health Effects

- American Cancer Society subjects enrolled in 1982 (>669,047) geocoded to baseline address
- Follow up with mortality linkage from 1982 to 2004 (105,039 deaths from Circulatory + Diabetic causes)
- Numerous covariate data available to control for confounding
- Control applied for 42 individual (smoking, occupational exposures, etc) and 8 ecologic confounders (unemployment, poverty, etc.) in standard and multilevel Cox models

INDIVIDUAL LEVEL COVARIATES:

Tobacco smoke variables:

1. Indicator variable for current cigarette smoker
2. Indicator variable for pipe or cigar smoker,
3. Current smoker's years smoked,
4. Current smoker's years smoked squared,
5. Current smoker's cigarettes per day,
6. Current smoker's cigarettes per day squared,
7. Indicator variable for former cigarette smoker,
8. Former smoker's years smoked,
9. Former smoker's years smoked squared,
10. Former smoker's cigarettes per day,
11. Former smoker's cigarettes per day squared,
12. Indicator variables for starting smoking before or after age eighteen,
13. Number of hours per day exposed to passive cigarette smoke.

Education variables:

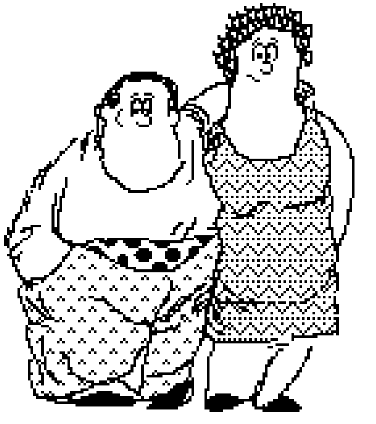
- Indicator variables for high school completed and more than high school completed, versus high school not completed

Marital status variables:

- Indicator variables for “single” and “other” versus married

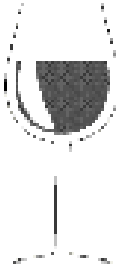
BMI:

- BMI and BMI squared



Alcohol consumption:

- Six variables including indicator variables for beer, liquor, and wine drinkers and non-responders versus non-drinkers



Occupational exposure:

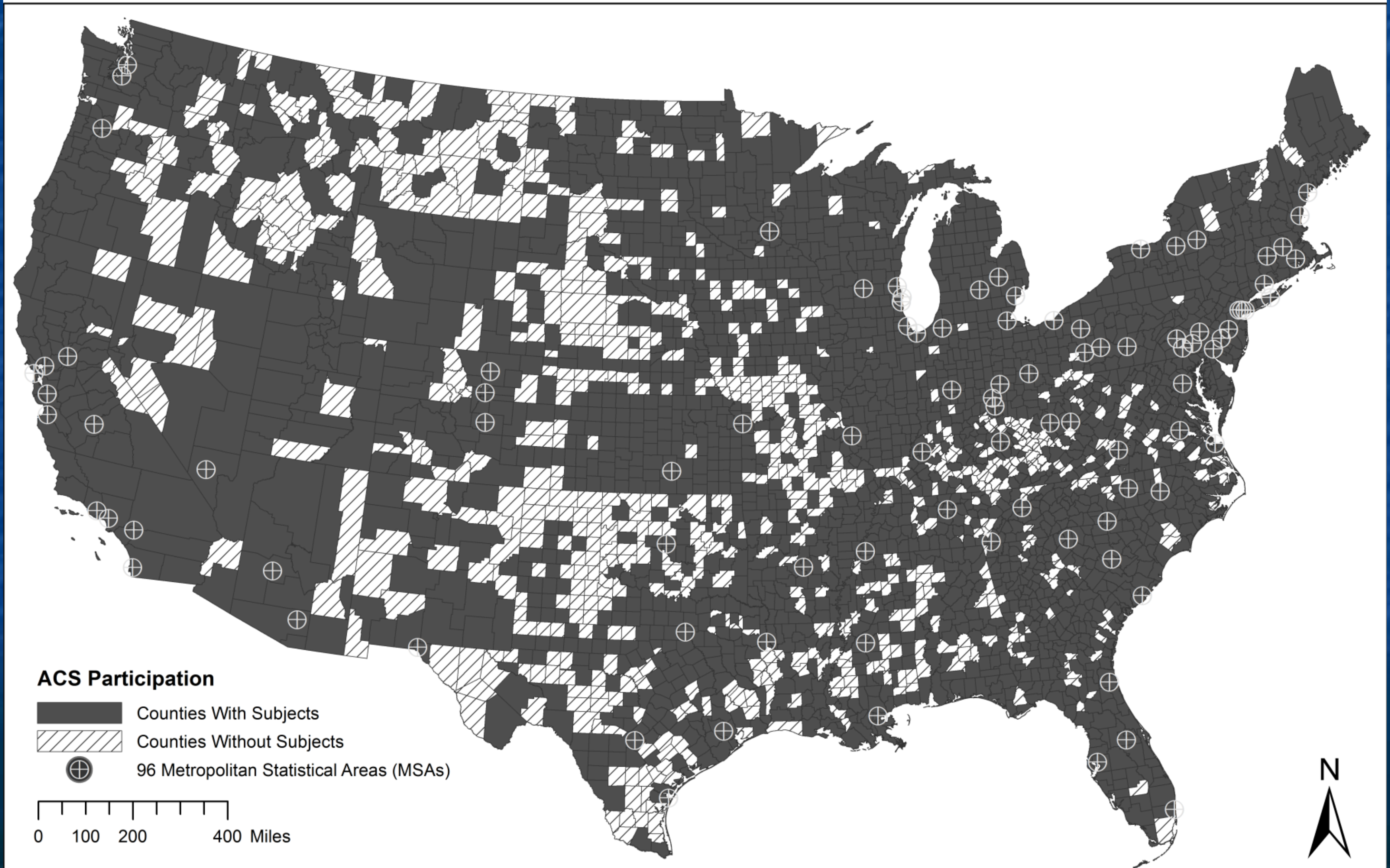
♦A variable that indicated regular occupational exposure to asbestos, chemicals/acids/solvents, coal or stone dusts, coal tar/pitch/asphalt, diesel engine exhaust, or formaldehyde

♦9 additional indicator variables that reflected an occupational dirtiness index

Diet:

♦Quintile indicator variables for each of two diet indices that accounted for fat consumption and consumption of vegetables, citrus and high-fiber grains were derived based on information given in the enrollment questionnaire.

U.S. Counties with ACS Subjects



Survival Model: Cox Random Effects Poisson

- Cox proportional hazards regression

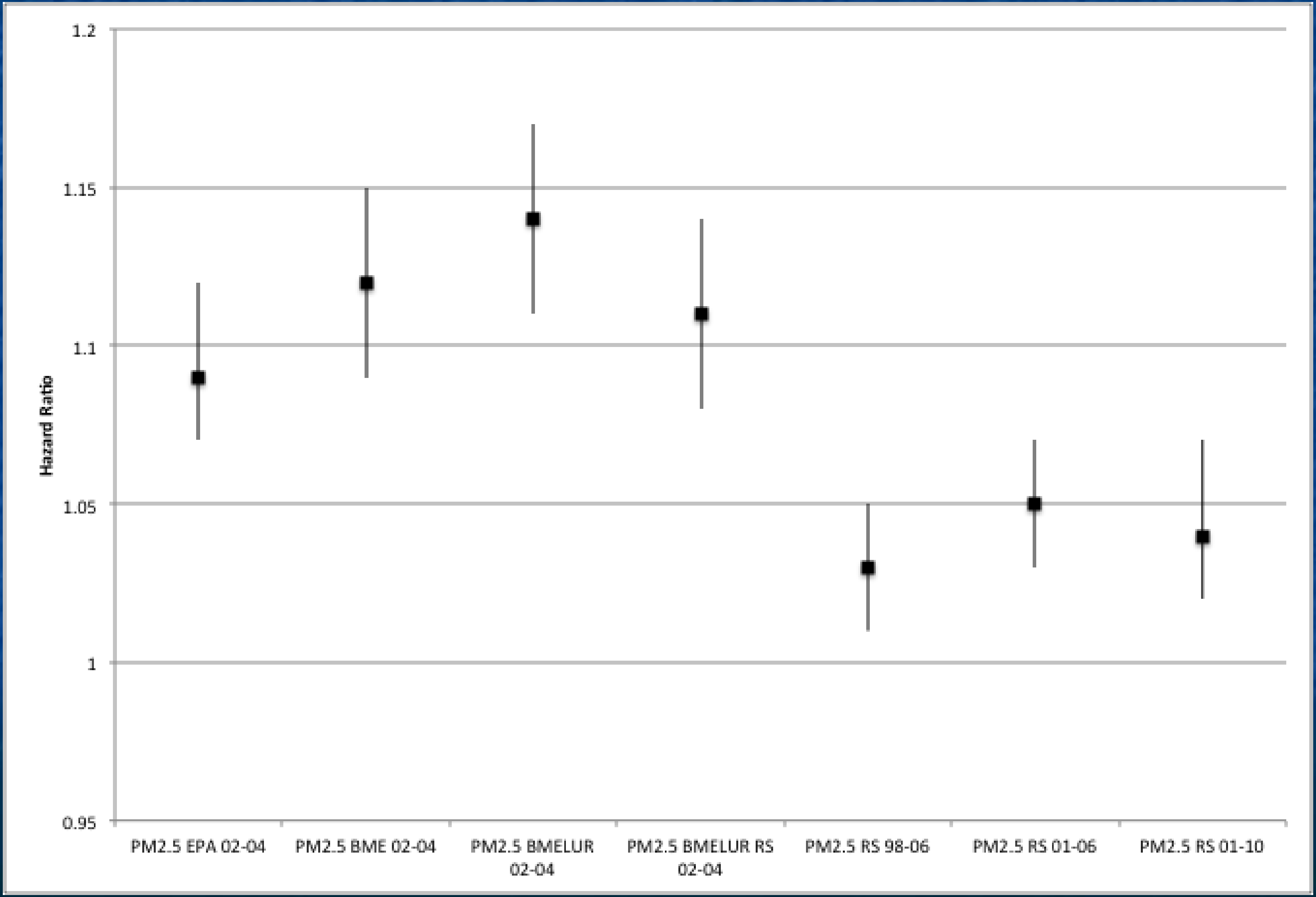
  $h_{ij\ s}(t)=h_{0\ s}(t)\eta_j\exp(\beta' x_{ij\ s})$

  - h_{ij} : hazard function for the i^{th} subject in j^{th} county
  - S : the stratum (age, race, sex)
  - $h_{0\ s}(t)$: the baseline hazard function
  - η_j : positive random effects with expectation 1
  - X_{ij} : risk factors for the response (air pollution, smoking)

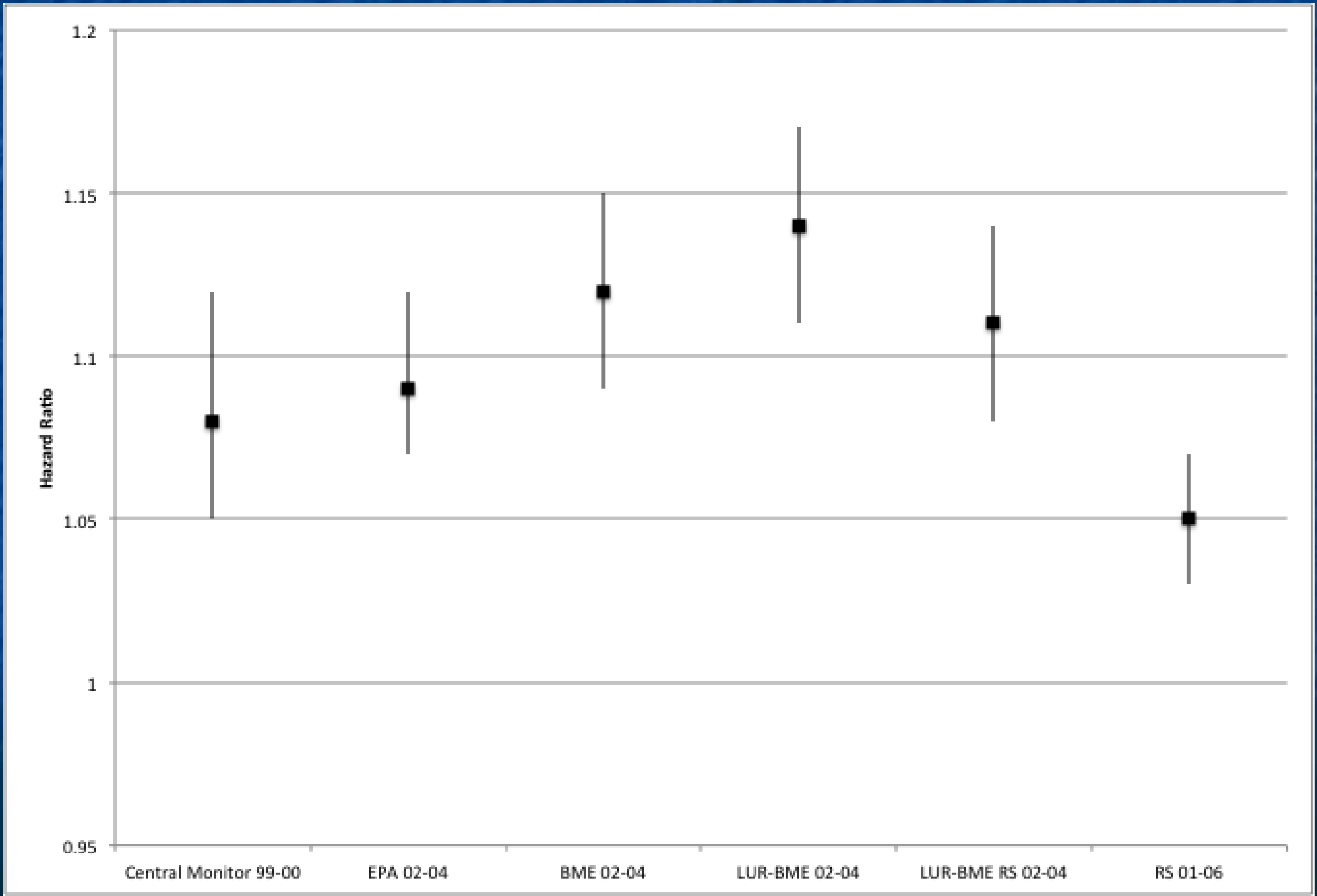
Correlations Among Exposure Estimates

	EPA	BME	BMELUR	BMELURRS	RS 98-06	RS 01-06	RS 01-10
EPA	-	0.89	0.84	0.85	0.61	0.63	0.63
BME		-	0.92	0.93	0.64	0.64	0.65
BMELUR			-	0.94	0.56	0.60	0.59
BMELURRS				-	0.60	0.66	0.62
RS 98-06					-	0.84	0.97
RS 01-06						-	0.87
RS 01-10							-

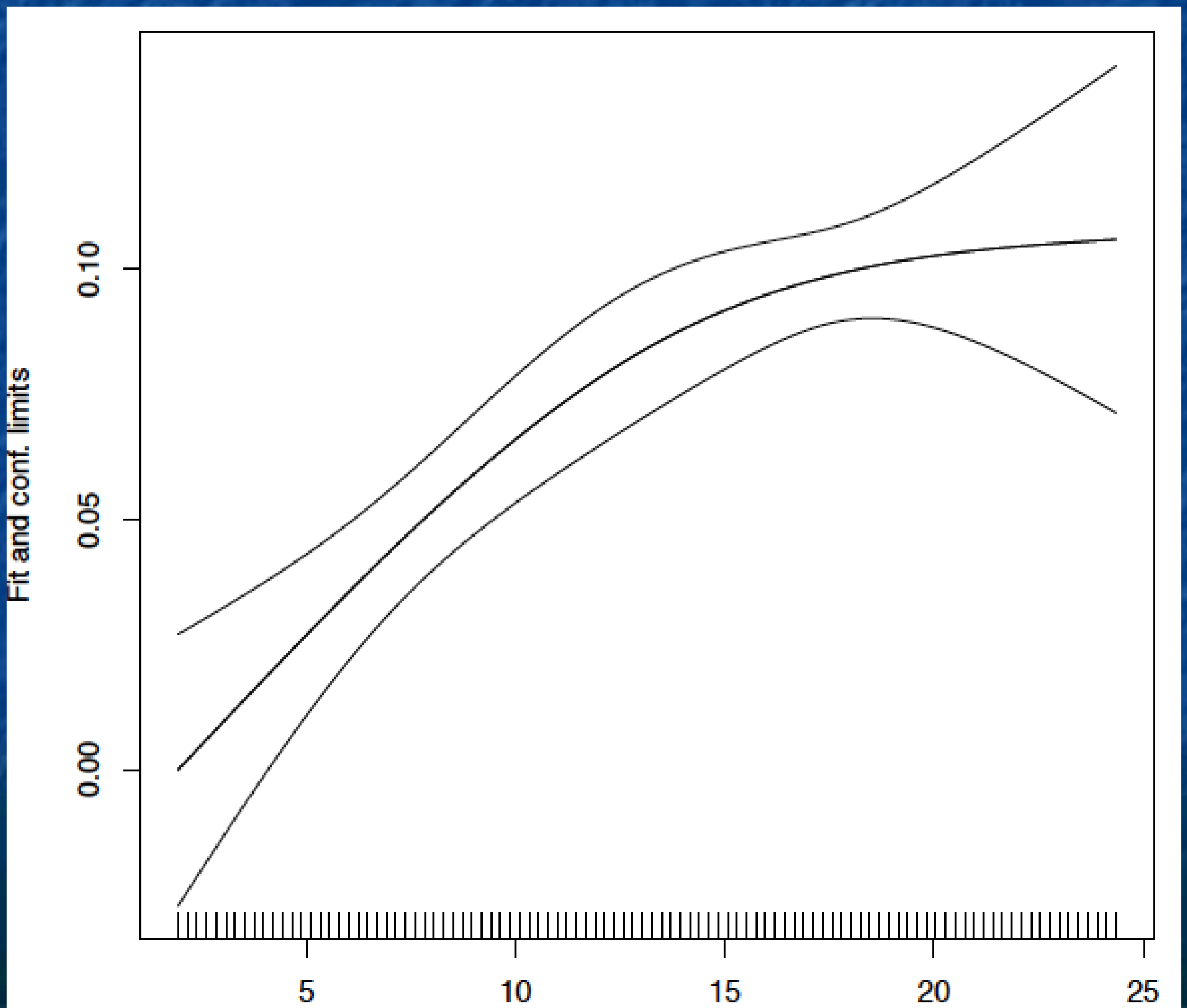
Results for Circulatory Death + Diabetes (10 ug/m^3)



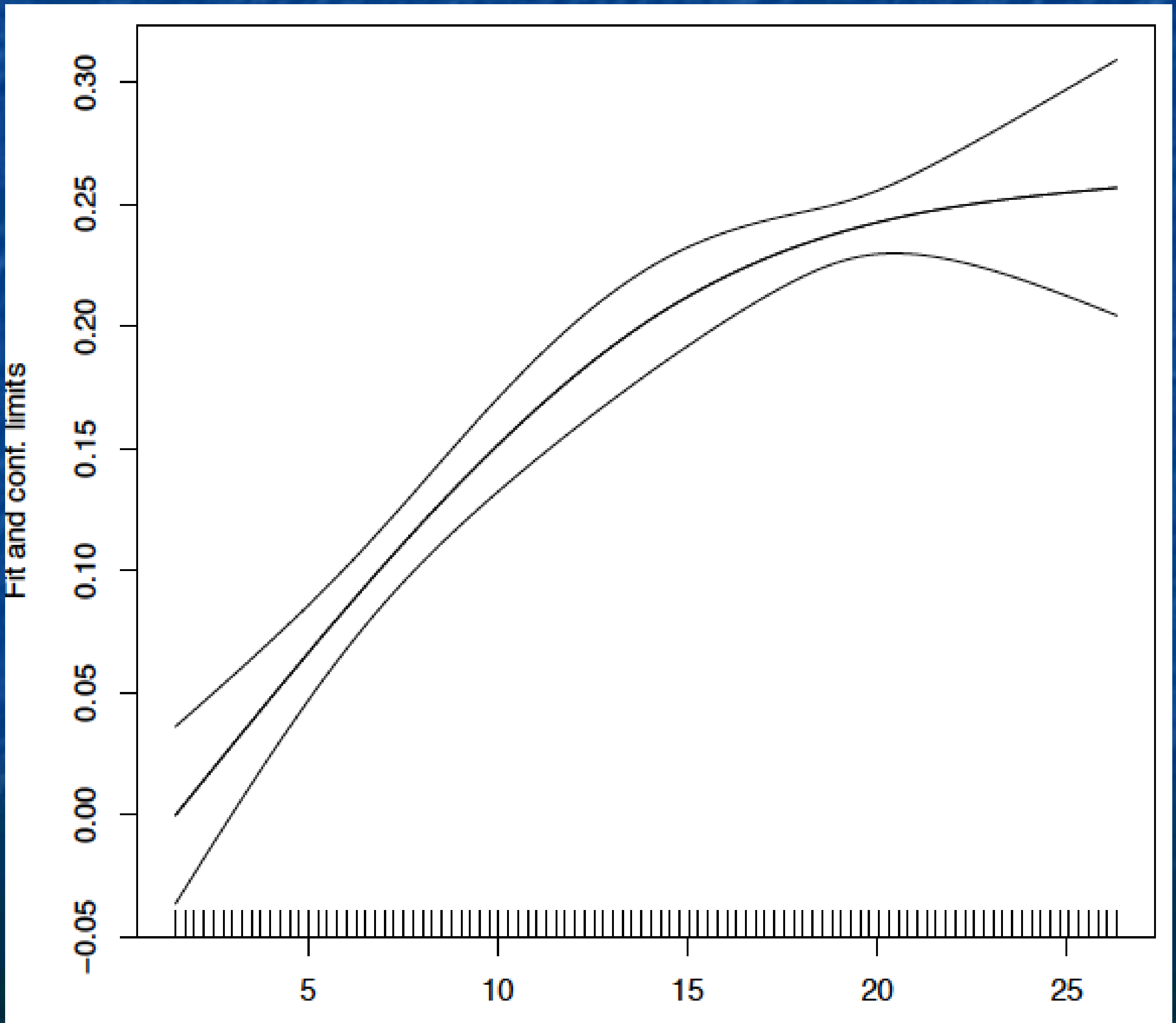
Results for Subjects with Central Monitors and Geocodes (N = 379,902)



Concentration-Response for Remote Sensing Steeper at Lower Levels



Concentration-Response for the BME-LUR Model (Similar but Steeper Overall)



Discussion

- All exposure models indicated association between death and $PM_{2.5}$ – comforting!!
- Risks vary by exposure model, but models with ground data produce higher risks
- Largest risks for models that detect small-area variation from traffic

Implications

- Suggests exposure models need to predict at fine spatial scale to give accurate risk estimates
- Critical to predict at scale of likely true variation ***for mixtures that are toxic***
- Current remote sensing models lack the that spatial resolution necessary to assess fine-area variation and may underestimate health effects

Other Implications

- Reliance on remote sensing only may lead to underestimates of effects
- May also have led to underestimates in Global Burden of Disease study

Future Directions

- More highly-resolved remote sensing estimates (1 km)
- Improving estimates of traffic with network kriging models
- Developing ensemble methods that use all exposure models simultaneously (like the climate change modelers)

Acknowledgement

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Co-Investigators and Student Researchers

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- Michael Thun, MD
- Jason Su, PhD
- Alberto Ortega PhD
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- Zev Ross, MS

THANK YOU!


Pacific Coast
1 SOUTH
EXIT ONLY
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NORTH
SOUTH

Results for Ischemic Heart Disease (10 ug/m^3)