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Monitor-to-monitor temporal correlation of air pollution in the contiguous US

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Numerous studies have reported short-term associations between ambient air pollution concentrations and mortality and morbidity. Particulate matter (PM) was often implicated as the most significant predictor of the health outcomes among the various air pollutants. However, a question remains as to the potential role played by the relative error of exposure estimation associated with each pollutant in defining their relative strengths of association. While most of the recent studies on PM exposure measurements have focused on the temporal correlation between personal exposures and the concentrations observed at ambient air quality monitors (within a few miles from the subjects), there have been few studies that systematically evaluated spatial uniformity of temporal correlation of air pollution within the scale of a city (several tens of miles) for which mortality or morbidity outcomes are aggregated in time-series studies. In this study, spatial uniformity of temporal correlation was examined by computing monitor-to-monitor correlation using available multiple monitors for PM_{10} and gaseous criteria pollutants (NO_2, SO_2, CO, and O_3) in the nationwide data between 1988 and 1997. For each monitor, the median of temporal correlation with other monitors within the Air Quality Control Region (AQCR) was computed. The resulting median monitor-to-monitor correlation was modeled as a function of qualitative site characteristics (i.e., land-use, location-setting, and monitoring-objective) and quantitative information (median separation distance, longitude/latitude or regional indicators) for each pollutant. Generalized additive models (GAM) were used to fit the smooth function of the separation distance and regional variation. The intercepts of the models across pollutants showed the overall rankings in monitor-to-monitor correlation on the average to be: O_3, NO_2, and PM_{10}, ($r \sim 0.6$ to 0.8) > CO ($r < 0.6$) > SO_2 ($r < 0.5$). Both the separation distance and regional variation were important predictors of the correlation. For PM_{10}, for example, the correlation for the monitors along the East Coast was higher by ~ 0.2 than western regions. The qualitative monitor characteristics were often significant predictors of the variation in correlation, but their impacts were not substantial in magnitude for most categories. These results suggest that the apparent regional heterogeneity in PM effect estimates, as well as the differences in the significance of health outcome associations across pollutants, may in part be contributed to by the differences in monitor-to-monitor correlations by region and across pollutants.
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Introduction

Numerous studies have reported short-term associations between ambient air pollution concentrations and mortality and morbidity (U.S. EPA, 1996). Particulate matter (PM) was often implicated as the most significant predictor of the health outcomes among the air pollutants examined. However, a question remains as to the potential role played by the relative error of exposure estimation associated with each pollutant in defining their relative strength of association. If one pollutant had larger errors in estimating population exposure than another pollutant, then the relative importance of the pollutants' underlying associations with health outcomes would be distorted in the regression analysis. Past time-series epidemiological studies of air pollution health effects could not take such exposure estimation errors into consideration because of lack of the information on the extent and the nature of such errors.

Much of the recent research on the PM exposure measurements has focused on the investigation of temporal correlation between personal exposures and the ambient air pollution. Typically, these studies measure daily personal exposures of air pollution (most often PM) for a number of people (~ 20 persons) for several weeks, and report temporal correlation between each individual's personal exposures and the ambient concentrations of that air pollutant measured at fixed outdoor monitors located within a few miles. Many of these studies (e.g., Lioy et al., 1990; Tamura et al., 1996; Wallace, 1996; Janssen et al., 1998, 1999; Ebelt et al., 2000) reported modest to reasonably high temporal correlations ($r \sim 0.35$–0.8) between personal PM exposures and the PM concentrations measured at the outdoor monitors. However, not all individuals had reasonably high correlations. Lioy et al. (1990) reported that only six of 14 subjects had a

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statistically significant relationship between outdoor and personal. Wallace (1996) reported a median r of 0.35 and a range of −0.17–0.76. Ebelt et al. (2000) reported a median r of 0.48 and a range of –0.68–0.83 for PM, but found that the ambient to personal correlations for sulfate were much higher, median $r = 0.96$ and range 0.66–1.00. The high correlations for sulfate are expected since there are few indoor sources of sulfate. Thus, it appears that for relatively diverse groups with reasonably high indoor PM contributions to their personal exposures, only a fraction of the subjects will have reasonably high correlations between personal and ambient concentrations. However, the correlations between ambient concentrations and personal exposure to *PM of outdoor origin* should be reasonably high (Mage et al., 1999). Some studies also investigated factors that can alter the correlation between personal exposure and ambient concentrations. For example, Suh et al. (1994) found that the correlation of indoor and outdoor sulfate (a component of fine particles of outdoor origin) was lower for homes with air conditioning, presumably due to lower air exchange rates. Also, Sarnat et al. (2000) reported that, in an analysis of nonsmoking subjects in Baltimore, personal exposure and ambient concentrations of $PM_{2.5}$ were better correlated for those with better-ventilated homes. These findings collectively lend support to the epidemiological associations of short-term health effects with PM of outdoor origin.

However, it should be noted that the distance between the subjects and the fixed outdoor monitors was, at most, a few miles in most of these PM exposure measurement studies. For example, in Janssen et al.'s (1998) study, they reported that all subjects lived at most 4 km (~2.5 miles) from the outdoor monitor. In contrast, in a typical time-series analysis of mortality or morbidity, the daily counts of death or disease outcome are aggregated for a geographic boundary (usually a county or a metropolitan area that consists of multiple counties) that can span many tens of miles. For example, Los Angeles County, the most populated county in the US, has an area of 4070 square miles (64 miles × 64 miles, if it were a square) as well as substantial topographic variation. Therefore, there are questions regarding the spatial uniformity of temporal correlation of air pollution across locations within such a scale, if health outcomes of people residing in such a boundary are to be aggregated and examined for associations with air pollution within the boundary. First, what is the extent of temporal correlation of concentration of air pollution between points within such a scale? Second, are there differences in the extent of temporal correlation across air pollutants? Additional issues include possible regional variation in spatial uniformity of temporal correlation in the US, and identification of monitor specific factors (e.g., whether a monitor is located in a residential area or industrial area) that can alter one monitor's correlation with others. Resolving these issues should complement the person-to-monitor correlations reported in recent studies, and help establish the link between personal exposures and population-based exposure estimates used in time-series studies, as well as providing guidance regarding the choice of monitors for epidemiological purposes.

We have previously reported results from an analysis of monitor-to-monitor correlations in seven North-Central States, IL, IN, MI, OH, PA, WI, and WV (Ito et al., 2001) for the period 1988–1990. In that study, O_3, PM_{10}, and NO_2 showed generally higher monitor-to-monitor temporal correlation (r: 0.8–0.6) than CO or SO_2 ($r < 0.5$). In this study, we extended the study area to the 48 contiguous US states and covered a longer period (1988–1997). Our main objective was to determine the difference, on the average, in the monitor-to-monitor correlation across pollutants after adjusting for covariates (i.e., a comparison of the intercepts in the regression across pollutants). Also, the regional variation of monitor-to-monitor correlation, if any, is of interest, because this may be a factor in explaining regional heterogeneity of air pollution health effects reported in the past analyses of multiple cities' data. Finally, identifying monitor characteristic factors that substantially affect the variation in monitor-to-monitor correlation is important in evaluating the suitability of a regulatory monitor for its applicability to epidemiological analyses.

Material and methods

Data

Air pollution data for PM_{10}, SO_2, O_3, NO_2, and CO were extracted from U.S.EPA's Aerometric Information Retrieval System (AIRS) for all the monitors in the contiguous U.S. states for years 1988–1997. The AIRS working file format AMP355 (24-h average for PM_{10} and 1-h average for gaseous pollutants were available) was used. From the hourly gaseous pollutant data, daily average values were computed and used in the subsequent analyses. Since most of the PM_{10} data were collected on an every-6th-day sampling schedule (gaseous pollutants data were collected every day) at most sites, the data analyses were to be conducted for the PM_{10} sampling days only for all the air pollutants, in order to use comparable sample sizes.

The AIRS database format AMP355 contained monitor characteristic data elements associated with each air pollution monitor. These include: *Land Use* (Residential, Commercial, Industrial, Agricultural, Forest, Desert, Mobile, or Not Reported); *Location Setting* (Urban, Suburban, Rural, or Not Reported); and, *Monitoring Objective* (Maximum Concentration, Population Exposure, Background, Source, Objective Changed, or Not Reported). The AIRS database also identified each site's Air Quality Control Region (AQCR). The AQCRs are EPA-designated regional boundaries that were established based on jurisdictional boundaries, urban-industrial concentrations, and other factors such as air sheds, for the

purpose of providing adequate implementation of National Ambient Air Quality Standards (NAAQS) (U.S. EPA, 1972). The AQCRs can be intra- or inter-state, and consists of multiple county boundaries. There were 225 AQCRs in this data set. These characteristics were used in the data analysis as group indices or indicator variables, or to stratify the data.

The database also contained the longitude and latitude of each monitor. The longitude/latitude information was used to compute the separation distance between each pair of monitors, as well as to characterize the resulting monitor-to-monitor correlation as a function of geographic location. In addition to longitude/latitude, the resulting monitor-to-monitor correlations were also classified according to the seven regional divisions that were used by health researchers (EPA, 1996b; Samet et al., 2000; Krewski et al., 2000). These regional divisions were used in order to facilitate comparison of the results of this study with those (exposure characterization and time-series health effects analyses) used in other studies. The seven regional divisions are shown in Figure 1, superimposed on the US map with the location of all the air pollution monitors used in the analysis.

Statistical Analysis

The data analysis consisted of: (1) computation of monitor-to-monitor temporal correlation; and, (2) regression of the median correlation of each monitor (with other monitors) on monitor characteristic variables. These analyses were conducted separately for each of five criteria air pollutants, that is, PM_{10}, SO_2, O_3, NO_2, and CO.

Since the main interest was the monitor-to-monitor temporal correlation in the geographic scale of the metropolitan area (to match time-series health effects analyses) or larger area (to examine measurement error for monitors that are "too far" from the population center), the temporal correlation was computed for all the pairs within a given AQCR. This restriction also made the computation of correlation feasible. Prior to computing monitor-to-monitor temporal correlation, the air pollution time-series from each monitor was detrended using smoothing splines of time, with a period corresponding to approximately 1 month and longer, in order to eliminate the influence of seasonal and longer-term cycles. Also, the temporal correlation was computed only when the pair of monitors had at least 60

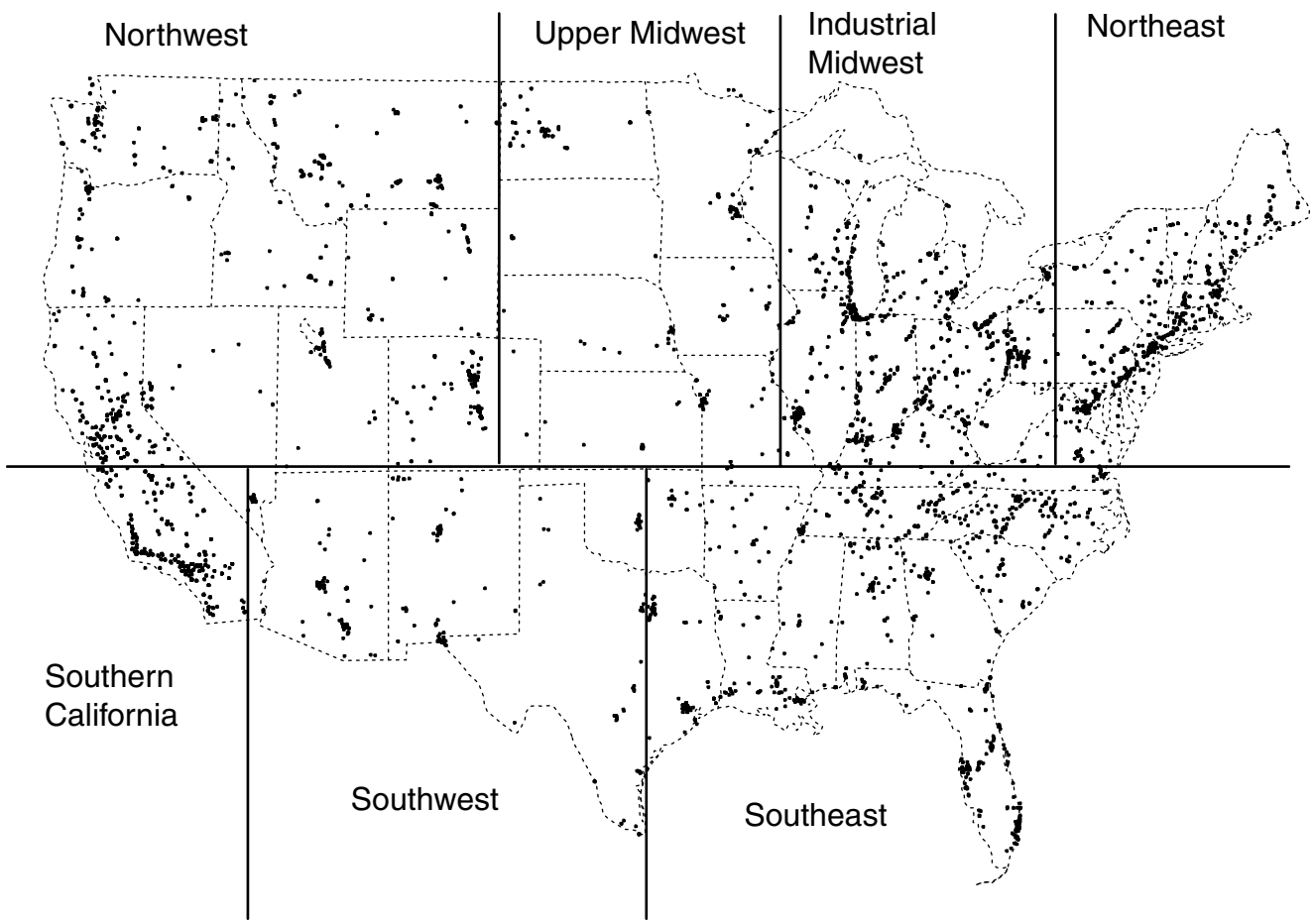

Figure 1. The seven regions and the location of all the air pollution monitors analyzed.

days of observations (approximately 1 year of every-6th-day samples). Once temporal correlation was computed for all the pairs of monitors within the same AQCR, the median correlation was computed for each monitor (that is, the median of a monitor's correlation with other monitors).

To quantitatively describe factors that explain the variation in monitor-to-monitor correlation, we next conducted regression analyses. The distribution of the median correlation was somewhat skewed to the right. However, the results from preliminary regressions indicated that the residuals of regressions with the monitor characteristic covariates were approximately normally distributed. Therefore, we then conducted regression analyses of the median monitor-to-monitor correlation (dependent variable) on monitor characteristic variables using a generalized additive model (GAM) (Hastie and Tibishirani, 1992). The GAM model allowed potentially nonlinear relationships between the median correlation and the explanatory variables. Local smoothing functions (e.g., Cleveland, 1979) were included in the GAM models. The statistical package, Splus (Insightful, 2001), was used for all the data analyses. To assure convergence of the GAM's iterative estimation procedure, the convergence criteria parameters were set as suggested by Dominici et al. (2002) as follows: epsilon $= 10^{-14}$; back-fitting epsilon $= 10^{-14}$; maximum iteration $= 1000$; and, back-fitting maximum iteration $= 1000$. The explanatory variables included qualitative monitor characteristic, the median separation distance for each monitor with others, "large" (the largest five percentile) or "small" (the smallest five percentile) variance of the monitor's data, and one of two ways to model regional variation in monitor-to-monitor correlation. Model specifications of these variables are described in the following.

The qualitative monitor characteristic variables were modeled using a smoothing spline function (as implemented in Splus as a function, 's') of a group of indicators, rather than with separate individual indicator variables. For example, the eight possible categories of the *Land Use* (described above) could be arbitrarily labeled from one to eight, and a smoothing spline of these levels were fitted using seven degrees of freedom. Likewise, the *Location Setting* (four categories) and *Monitoring Objectives* (six categories) were fit using smoothing splines with degrees of freedom of three and five, respectively. A smoothing function of median separation distance was included in the regression with locally estimated smoothing (as implemented in Splus as the function 'lo()'). The correlation was assumed to decline uniformly as a function of a separation distance, and therefore, a relatively wide span of 0.4 was chosen for all the air pollutants. Based on our previous analysis using a smaller geographic coverage of North-central states (Ito et al., 2001), having a very large or small variance of temporal fluctuations was a significant predictor of a low correlation. Therefore, indicator variables for the monitors with the largest and smallest variance in the five percentiles were also included in the regression model.

Regional variation, or heterogeneity, of the monitor-to-monitor correlation was modeled using two alternative approaches: (1) using the seven regional categories; (2) applying a smooth function of longitude/latitude. As with the qualitative monitor characteristic variables, the seven regional categories were arbitrary numbered and modeled as a group using the smoothing spline function with six degrees of freedom. Since the regional differences in the distribution of median separation distance may influence the estimate of regional variation, even with the simultaneous inclusion of median distance in the model, the analysis was also repeated using the data stratified by the separation distance. The data were split in half at the median, and also in fourths at quartile values. In the model using smoothing function of longitude/latitude ('loess' in Splus), a series of spans (0.4, 0.3, 0.2, 0.10, 0.05, 0.02, and 0.01) were used because we did not have strong assumptions regarding the pattern and smoothness of the regional variation pattern. The span for the final model was chosen for each air pollutant based on: (1) a visual inspection of the spatial pattern of the predicted values; (2) distribution of the predicted values; and (3) the generalized cross-validation values (Hastie and Tibshirani, 1990) computed for each of the spans. Thus, the variables described in the previous paragraphs were simultaneously included in the regression model with either of these two geographic variables separately.

Results

Table 1 shows the number of monitors used in the computations of monitor-to-monitor temporal correlation (number of observations more than 60 days). PM_{10} had the

Table 1. Number of monitors used in the computations of temporal correlation by region.

Pollutant	Northeast	Industrial midwest	Southeast	Upper midwest	Southwest	Southern California	Northwest	Total
PM_{10}	299	414	325	129	124	81	520	1892
O_3	181	290	265	34	72	110	181	1133
SO_2	199	330	166	73	26	74	101	969
NO_2	68	79	42	15	19	58	71	352
CO	100	122	98	37	52	56	167	632

largest number of monitors and NO_2 the least. The number of monitors in these seven regions were not evenly distributed, with the upper Midwest and Southwest regions containing the two smallest numbers of monitors. As can also be seen in Figure 1, the density of monitors varies from region-to-region. It should be noted that the monitor-to-monitor correlation was computed only for those pairs within the same AQCR, limiting the scale of separation distance within the region. The medians of the within-AQCR median separation distance for PM_{10}, SO_2, O_3, NO_2, and CO were 26, 19, 26, 18, and 11 miles, respectively.

Figure 2 shows the individual correlation coefficients of all the pairs of monitors (within the same AQCR) vs. their separation distance, as well as smoothed lines of these points. It can be seen that, overall, PM_{10}, O_3, and NO_2 appear to have similar extent of monitor-to-monitor correlation (~ 0.8) when separation distance is very short (<10 miles), whereas SO_2 and CO showed generally smaller correlation. SO_2 had

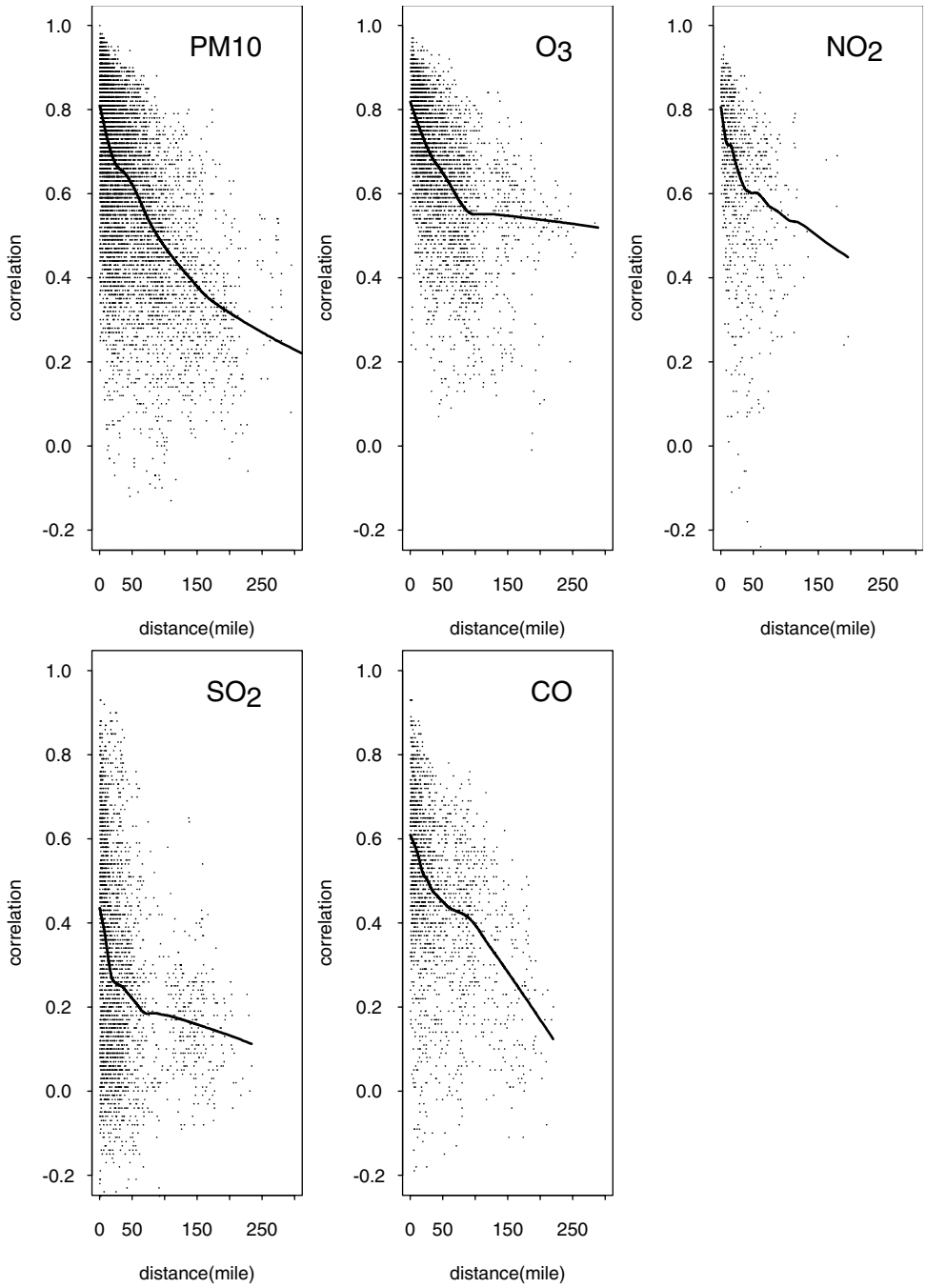

Figure 2. Monitor-to-monitor temporal correlation vs. separation distance for all the pairs of monitors analyzed.

the widest range of correlation. All the pollutants show declining correlation as the separation distance widens, but the apparent slopes seen here may be misleading as they are not adjusted for regional variation in correlation. From these individual correlation coefficients, the median was computed for each monitor, and used in the regression models as described in the following. It should be noted that the apparent slopes of correlation vs. separation distance in Figure 2 are not adjusted for site-specific variables and regional indicators. Such adjustments are conducted in the subsequent regression models.

Figure 3 shows the fitted monitor-to-monitor correlations and their 95% confidence intervals for all the explanatory variables (fitted simultaneously) from the PM_{10} regression model in which regional variation was modeled with seven regional indicators. Note that, while some of the qualitative monitor characteristic variables (i.e., Land Use, Location Setting, and Monitoring Objectives) showed significant

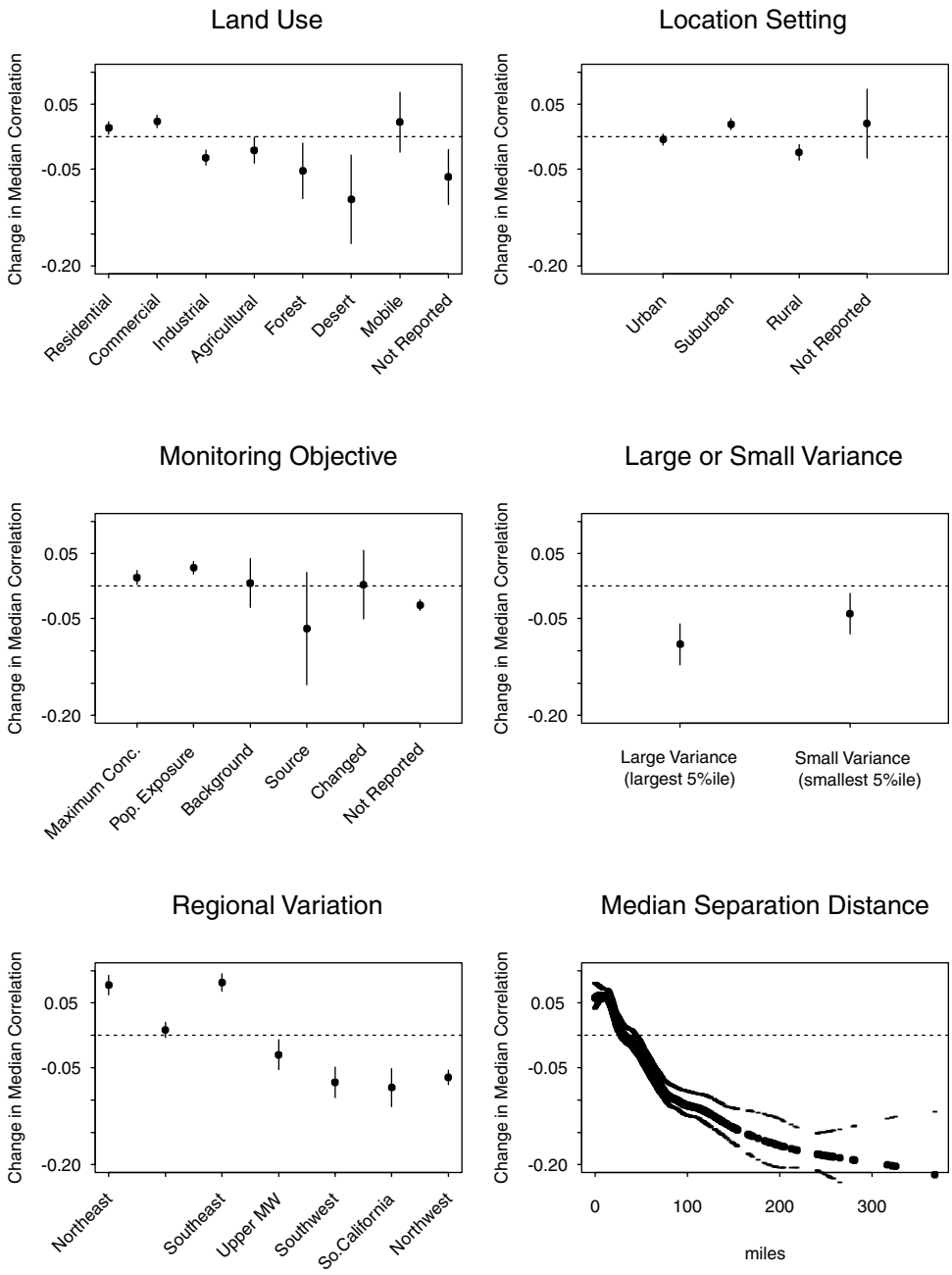

Figure 3. Fitted median correlation in the regression model with all the covariates for PM_{10}.

differences (e.g., "residential" is higher than "industrial" in Land Use), their magnitude of impacts were mostly not substantial (less than 0.1 difference in correlation). The wider confidence bands in some of the categories reflect their relatively small number of observations in those categories, and therefore do not contribute substantially to the overall variance. The pattern of these qualitative monitor characteristic variables in other pollutants were generally similar to those for PM_{10} (e.g., lower correlation for "desert", etc.), or did not show a distinct pattern (results not shown). The exception was the pattern in Location Setting for NO_2 and CO, where "rural" monitors showed significantly low correlation ($\sim$0.1 lower). Both very large and small variance of temporal fluctuations explained lower correlation for PM_{10}. For NO_2, SO_2, and CO, the small variance of temporal fluctuations also explained lower correlation. The separation distance, as modeled with a smooth function, was an important predictor of reduction in correlation for all the pollutants. The reduction in correlation in 30 miles, as computed as the difference between the predicted correlation at 5 and 35 miles, were 0.06, 0.12, 0.06, 0.06, and 0.13 for PM_{10}, SO_2, O_3, NO_2, and CO, respectively. Note that these slopes are considerably shallower than the apparent slopes observed in the raw data in Figure 2, suggesting that at least some of the slope could be explained by the site-specific variables.

Table 2 shows the intercepts in the regression results for the five pollutants using the two alternative regional variation models. It can be seen that the two alternative models can make a difference of as much as 0.1. In both models, however, SO_2 and CO were the two pollutants with the lowest correlations.

Table 3 summarizes the relative variance contribution from each of the fitted explanatory variables for regressions with two alternative regional variation models. Note again that the regional variation and the median separation distance are the two important explanatory variables for all the pollutants, except for NO_2, for which Location Setting was also an important explanatory variable. The amount of variance explained by the two alternative regional variation models was somewhat different for PM_{10} and O_3. For PM_{10}, the smooth function of longitude and latitude fitted better than the seven-region indicator model. For O_3, the seven-region indicator model explained more variance than the smooth function model. For CO, the two regional variation models showed comparable fits but affected the variance explained by the separation distance. These results do not seem to suggest any overall preference of one regional variation model over the other. Overall, about 30–40% of the variance in the median monitor-to-monitor correlation could be explained by these regression models.

Table 2. Intercepts of the median correlation regression models.

Pollutant	Model with seven region indicators Intercept (95% CI)	Model with smooth function of longitude/latitude Intercept (95% CI)
PM_{10}	0.74 (0.71, 0.76)	0.64 (0.62, 0.66)
O_3	0.82 (0.80, 0.84)	0.71 (0.69, 0.72)
SO_2	0.48 (0.44, 0.51)	0.38 (0.35, 0.41)
NO_2	0.69 (0.64, 0.74)	0.71 (0.66, 0.75)
CO	0.49 (0.44, 0.53)	0.57 (0.53, 0.60)

Figure 4 shows the fitted regional pattern of correlation (adjusted for other covariates via regression) across pollutants using the seven regional indicators. Note that an overall evaluation of correlation across pollutants requires adding intercepts for each pollutant to these values. For example, in Northeast, the monitor-to-monitor median correlation is approximately 0.08 higher than the baseline (intercept). Since the intercept is 0.74 for PM_{10}, (from Table 2), the "average" correlation of PM_{10} is about 0.82 in this region. The largest regional variation was observed for SO_2, with a difference in correlation of 0.4 between Northeast and Upper Midwest or Southwest. PM_{10}, O_3, and SO_2 showed a similar pattern in that Northeast had a higher correlation than Western regions (Southwest, Southern California, and Northwest).

Although the effects of separation distance was modeled in the regression, it was still possible that the higher monitor-to-monitor correlation in eastern regions for PM_{10}, O_3, and SO_2 may have been due to the relatively high density of monitors in that region. Therefore, the regression analysis with the seven regional indicators was repeated using data stratified by the median separation distance in halves (at the median), and in fourths (at quartiles). Figure 5 shows the PM_{10} results for which the data were split in half at the median of the median separation distance. The pattern of higher values in eastern regions and lower values in western regions are seen in both subsets, but more so in the subset with larger separation distance. In the results for subsets stratified by quartiles of the separation distance (not shown), a similar pattern was seen, but most pronounced in the subset with the largest quartiles of separation distance. Thus, the contrast between eastern regions and western regions does not appear to be due to the difference in monitor density.

In the models with a smooth function of longitude/latitude, the fitted regional patterns of correlation were generally consistent with those observed in the models using the seven regional indicators. Figure 6 shows the fitted and interpolated regional pattern in monitor-to-monitor correlation for the five air pollutants, adjusting for other covariates. In these models with smooth functions of longitude/latitude, the span of 0.05 was chosen for PM_{10}, O_3, SO_2, and CO; and, span of 0.2 was chosen for NO_2. For all the pollutants, there appears to be some influence from factors related to topographical features.

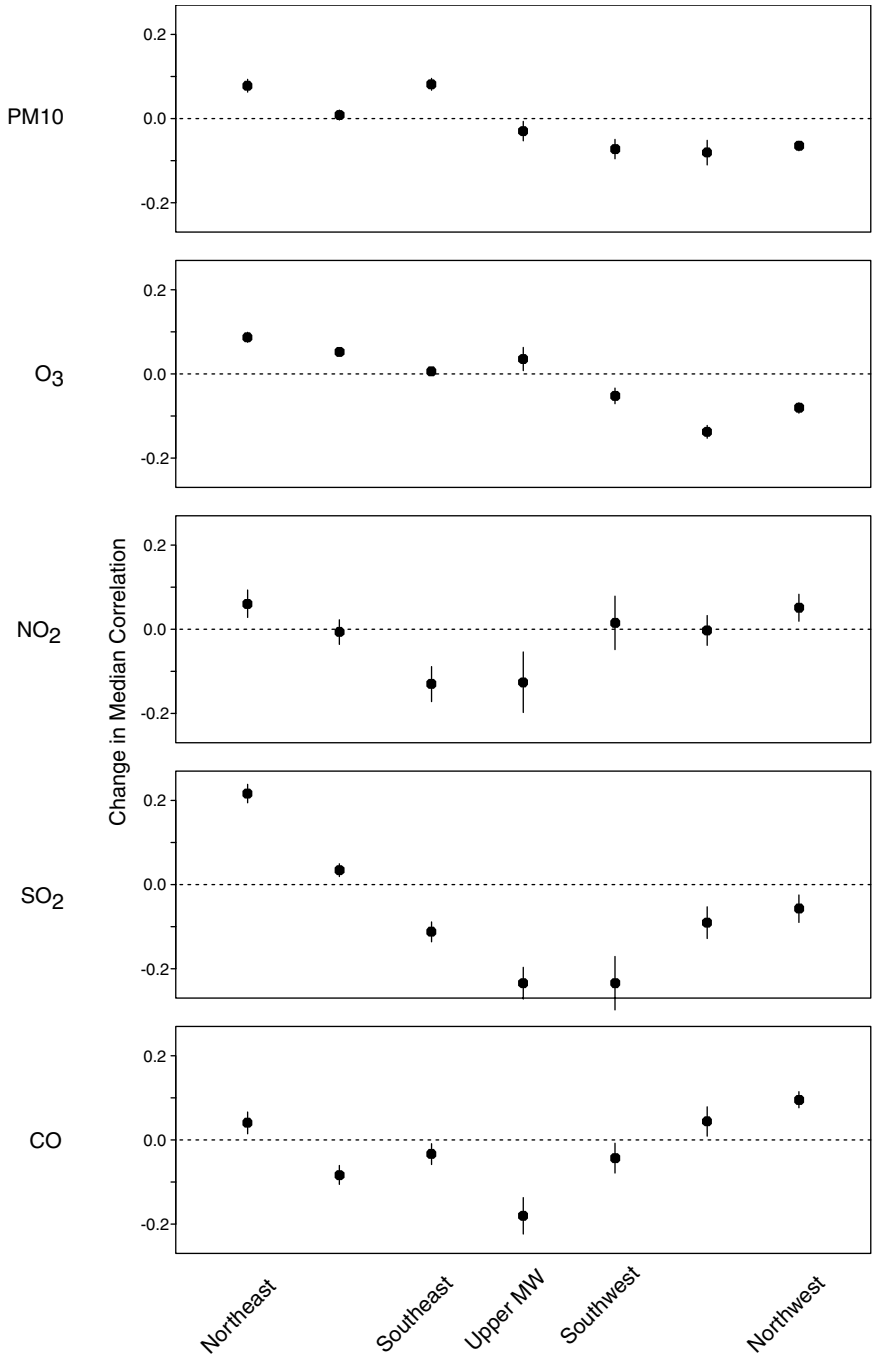

Figure 4. Fitted regional variability in median monitor-to-monitor correlation.

Discussion

The results of this analysis of the entire contiguous US data show some patterns similar to our earlier analysis of data for a smaller geographic coverage (seven North-Central US states): (1) CO and SO_2 showed, on the average, lower monitor-to-monitor correlation than PM_{10}, O_3, and NO_2; (2) the separation distance was an important predictor of drop in correlation; and, (3) the influence of the qualitative site characteristics such as location setting on correlation was not substantial for common categories. In this study, regional variation of monitor-to-monitor correlation was also investigated, and was found to be an important feature. For example, while SO_2 may have poor monitor-to-monitor correlation in general, it may have correlation comparable to PM_{10}, O_3, or NO_2 in some of the Northeast cities. The

Table 3. Percent variance contributions from the fitted covariates in the regression model.

Pollutant	Regional model[a]	Land use	Location setting	Monitoring objective	Regional variation	Separation distance	Large variation	Small variation
PM_{10}	A	1.8	0.8	1.7	10.5	12.0	0.9	0.2
	B	1.8	0.6	1.7	16.3	10.7	1.1	0.1
O_3	A	2.9	0.3	1.6	25.3	13.9	0.1	0.0
	B	3.0	0.3	1.9	14.8	18.8	0.5	0.0
SO_2	A	1.0	1.0	1.2	35.7	3.3	0.1	0.6
	B	0.6	1.7	1.2	29.7	4.5	1.0	0.1
NO_2	A	1.6	12.2	1.1	12.3	7.6	0.5	0.7
	B	1.1	12.3	0.5	10.8	7.8	0.1	1.1
CO	A	0.8	5.1	1.0	19.9	17.3	0.1	1.4
	B	1.1	4.7	0.9	19.2	8.3	0.1	1.9

[a]Note: Model A: seven regional indicator variables; Model B: loess smooth function of longitude and latitude.

difference in monitor-to-monitor correlation between Northeast and upper Midwest for SO_2 was as large as 0.4, likely explaining a major fraction of the scatter seen in the raw monitor-to-monitor correlation. Thus, the results of this study show that the overall difference in monitor-to-monitor correlation across the air pollutants, but also show their regional variation, both of which may be important in assessing the apparent heterogeneity of air pollution effects across cities in the US.

The differences in monitor-to-monitor correlation across the pollutants and regions observed in this analysis can, to some extent, be explained by the difference in nature and sources of these pollutants. CO and SO_2 are both primary pollutants, and the impacts from local sources are expected to be greater than the secondary pollutants formed in the atmosphere like NO_2 or O_3, which are likely more uniformly distributed within a city. Some of the PM_{10} can be from local sources, but it also contains regional secondary sulfate and organic fine particles. Since the larger influence of the regional secondary aerosol would increase the monitor-to-monitor correlation, the regions where secondary aerosol is prevalent should also find generally high monitor-to-monitor PM correlation. In fact, the pattern of the regional variation of correlation for PM_{10} (north- and south-eastern regions having higher monitor-to-monitor correlation than western regions) found in this study is consistent with such speculation. The regional variation in monitor-to-monitor correlation for other gaseous pollutants may in part be related to their concentration levels and their variability. For example, the relatively higher monitor-to-monitor correlation for SO_2 in the Northeast may be due to its relatively high concentrations ($\sim$7 ppb as annual average of daily values) as well as smaller variability of mean levels across monitors within the region. A related issue is the differential influence of the signal-to-noise ratios (i.e., observed levels vs. detection limits) across pollutants on the corresponding monitor-to-monitor correlations. For example, according to the information retrieved from AIRS database, the minimum detection limit for CO was 0.5 ppm for 24-h average measurements, which is above the mean levels for many of the CO monitors in this data set. Also, in our results, the small variation of CO (i.e., low levels) was a significant predictor (though its magnitude was not substantial) of low monitor-to-monitor correlation. Thus, the lack of signal (in relation to the detection limit) alone may explain some of the low correlations. For other pollutants, the mean levels were mostly above their detection limits.

Examining the relationship between the monitor-to-monitor correlation and the short-term risk estimates obtained in time-series studies is not straightforward because the spatial heterogeneity of temporal fluctuations of an air pollutant is only one component of exposure measurement error for the population. The other components include the discrepancy between personal exposure and ambient concentrations. A development of conceptual framework and a systematic evaluation of this type of error were conducted by Zeger et al. (2000). In their model, the pollution measurement difference between personal exposure and the average of multiple monitor measurements was decomposed into three components: (1) the error due to having aggregate rather than individual exposure data; (2) the difference between the average personal exposure and the true ambient pollutant level; and, (3) the difference between the true and the measured ambient concentration. They then illustrated that the first and the third components are of the Berkson-type error, and therefore are likely to have relatively small effect on risk estimates. However, the Zeger et al. model assumed, as mentioned in their paper, that a high degree of spatial homogeneity in ambient levels existed, and, for the "measured ambient concentration", the average of multiple monitor measurements was assumed to be available. Thus, the component of exposure error, as exhibited in poor monitor-to-monitor correlation, was not examined, and the relative importance of these different components of exposure error has not, to date, been systematically evaluated.

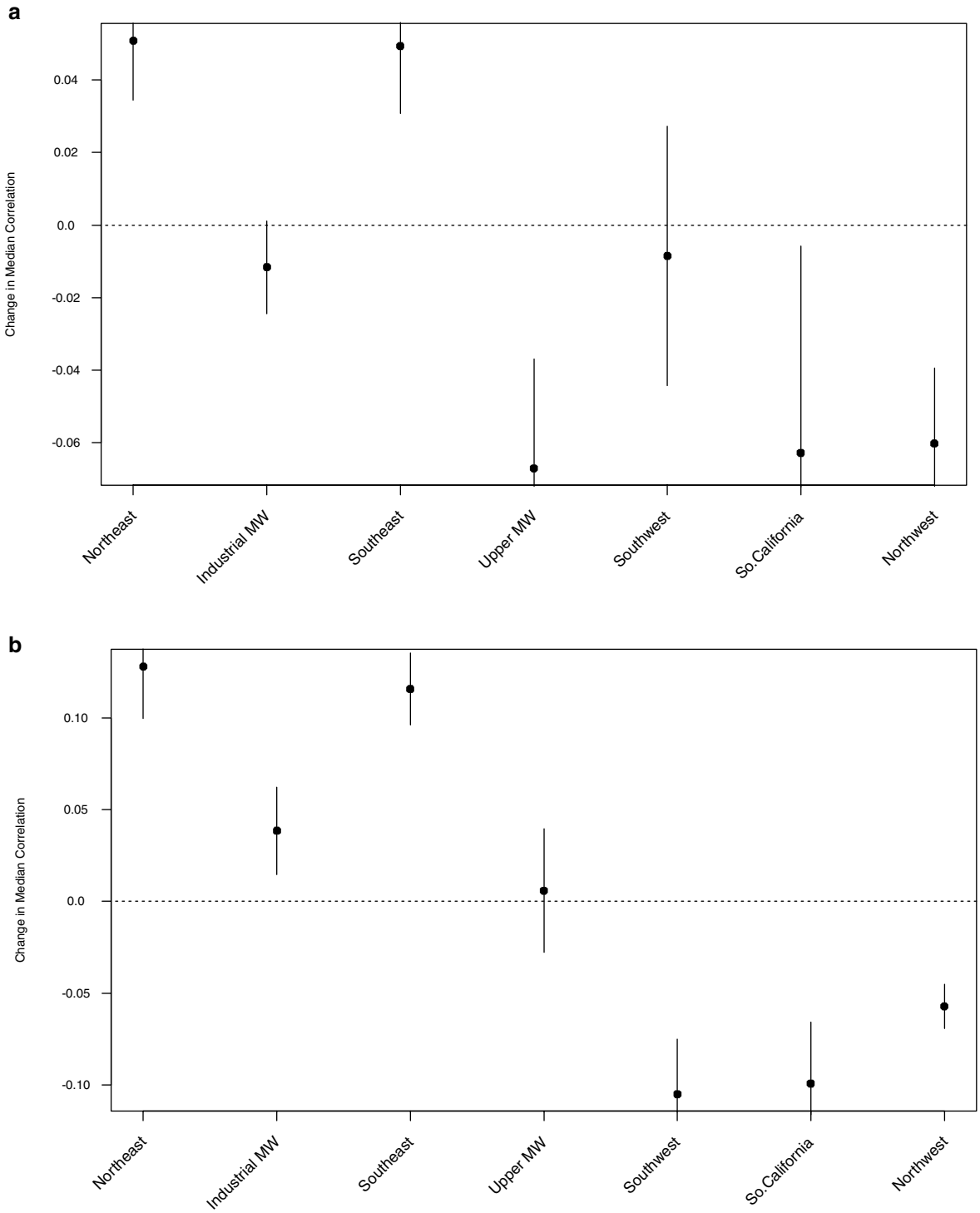

Figure 5. Regional variation in monitor-to-monitor correlation for PM_{10} stratified by separation distance range. (a) Influence of Region on correlation for median separation distance $<=25$ miles. (b) Influence of Region on correlation for median separation distance >25 miles.

There has been an attempt to examine the effect of monitor-to-monitor correlation on the PM_{10} mortality relative risk estimates. Samet et al. (2000) explored the potential effect modification of PM_{10} relative risks by regressing the PM_{10} coefficients from 90 largest US cities on the city-specific explanatory variables in their second-stage regression models. The explanatory variables included the mean levels of PM_{10} and gaseous pollutants, the median of

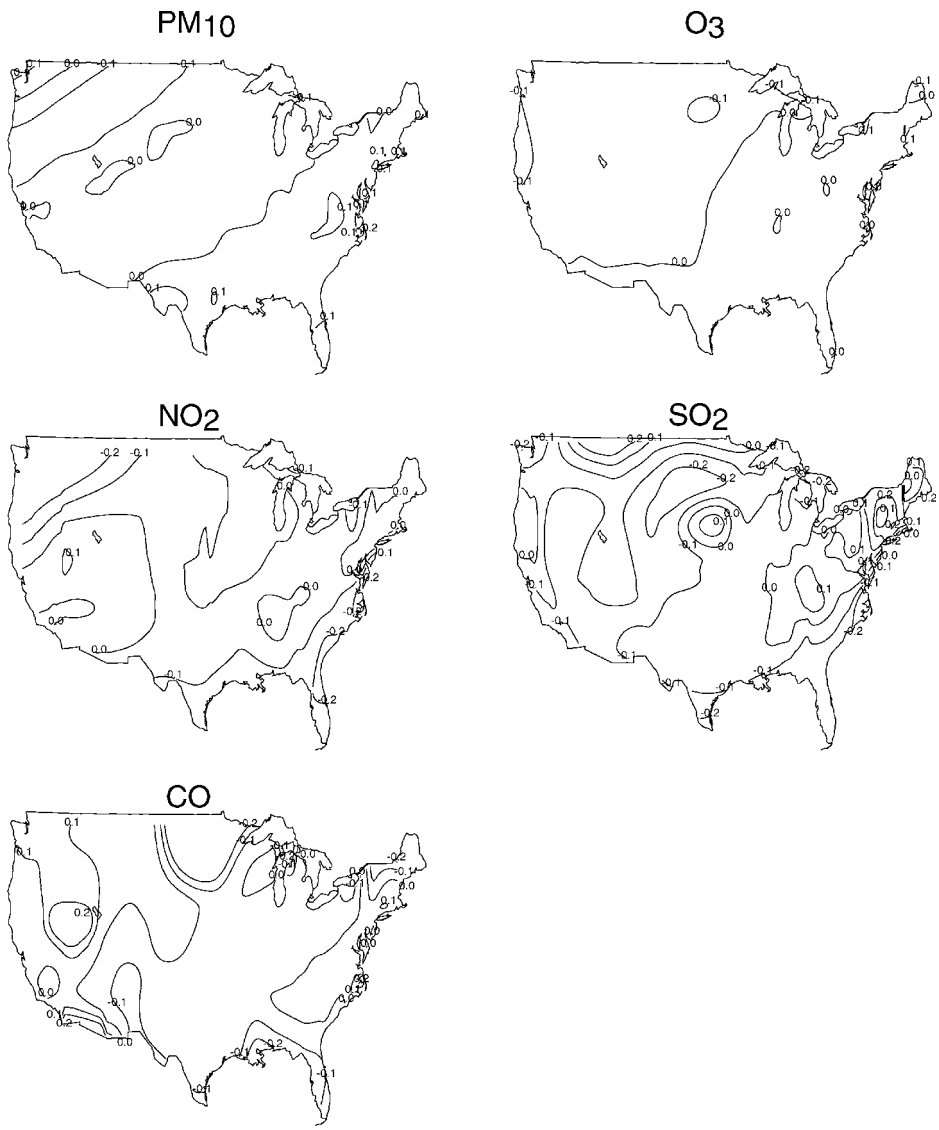

Figure 6. Fitted and interpolated surface of regional variation in monitor-to-monitor correlation.

the monitor-to-monitor correlation, the number of monitors, mortality rate, sociodemographic variables such as median household income, etc. While the median monitor-to-monitor correlation was one of the variables remained in the best-fitting models, the only statistically significant explanatory variables were the mean PM_{10} levels (negatively associated with PM_{10} risk estimates) and mean NO_2 levels (positively associated with PM_{10} risk estimates). Samet et al. concluded that the largest PM_{10} effect was evident in the Northeast, but they did not identify any factors that could explain the heterogeneity of PM_{10} effects across cities. It should be noted, however, that the PM_{10} and gaseous pollutants' data were averaged across multiple monitors for each city, and the number of available monitors varied from one to 30 in these cities. If each monitor has an associated error in representing the citywide temporal fluctuations of air pollution, and if averaging across monitors reduces the error, then the reduction in error in the averaged data would depend on the number of monitors. Therefore, examining the effects of error on the estimated PM_{10} risk estimates (that were computed from the multimonitor-averaged data) would require modeling the interaction of the median monitor-to-monitor correlation and the number of monitors. Thus, including the number of monitors and the median monitor-to-monitor correlation in the second stage regression in the Samet et al. study may not have detected the possible effect of exposure error. An alternative (and more direct) approach would be to estimate the pollution risk from each individual

monitor, and then to evaluate the relationship between the estimated risks and the estimated exposure error. We are currently applying this approach using the nationwide database developed in this project.

The differences in monitor-to-monitor correlation across pollutants observed in this study also have some implications in the interpretation of air pollution epidemiological studies. The difference in relative significance of associations with health outcomes across pollutants may in part be explained by the differences in the relative error of exposure estimates across pollutants, as exhibited in monitor-to-monitor correlation. Reviews of past epidemiological studies in the US (e.g., U.S. EPA, 1996a, b) suggest that generally stronger health outcome associations were found for PM indices than for SO_2 or CO, which is consistent with the higher monitor-to-monitor correlation found for PM_{10} than for SO_2 or CO. It should be noted, however, that the differences in person-to-monitor correlations across pollutants might also influence mask or distort the pollutants' associations with health outcomes. In a recent study (Sarnat et al., 2001) in Baltimore, MD, in which ambient concentrations and personal exposures were compared for $PM_{2.5}$, O_3, NO_2, and SO_2, they found that ambient concentrations were not associated with their corresponding personal exposures for any of the pollutants except $PM_{2.5}$. They also reported that ambient concentrations of gaseous pollutants were associated with personal $PM_{2.5}$ exposures, suggesting that the ambient gaseous pollutants may distort the $PM_{2.5}$ effects in time-series epidemiological models with multiple pollutants. However, complex intercorrelations among the ambient concentrations and personal exposures of PM and gaseous pollutants may vary regionally due to the regional differences in ventilation rates and levels of pollutants. Therefore, a more comprehensive assessment of the relative influence of person-to-monitor correlation and monitor-to-monitor correlation on health effects analysis will need exposure measurement data from a range of locations and regions.

The findings from this study also provide some insights into the design of air quality monitor network that considers epidemiological investigations as well as compliance with ambient air quality standards. The lower monitor-to-monitor correlations observed for the pollutants with stronger local impacts such as CO or SO_2 suggest that more monitors may be required to obtain the same level of precision in exposure estimates as for other pollutants. Conversely, in cities where very high monitor-to-monitor correlations were observed for PM or O_3, the available monitoring network may contain redundant monitors. We note, however, that in this study, we considered only temporal monitor-to-monitor correlation, which ignores the difference in absolute levels of pollutants. The absolute levels of pollutants can be important in comparing the resulting health risk estimates obtained from individual monitors. For example, in the Lippmann et al. (2000) analysis of Detroit mortality data, it was reported that, while the risk estimates obtained from each of 14 TSP monitors were comparable if the risk estimates were computed per comparable distributional increment (i.e., 5th-to-95th percentile) of TSP at each monitor, the estimated risk estimates varied by a factor of two when they were computed per same mass basis because the absolute mean levels of TSP among the 14 TSP monitors varied by a factor of two. Thus, evaluating the error in exposure estimates using monitor-to-monitor temporal correlation can depict only the factors that affect significance of associations with health outcomes, but not the size. A more comprehensive evaluation of exposure error related to ambient concentrations may also need to incorporate representativeness of monitors (Chan and Hwang, 1996), or redundancy of monitors (Hwang and Chan, 1997).

The monitor-to-monitor correlations found in this study, on the average, ranged from ~ 0.4 to ~ 0.8, across pollutants. These correlations were also influenced by the separation distance and by regional variation. For PM_{10}, the monitor-to-monitor correlations were on the average ~ 0.6–0.7 depending on the model. The person-to-monitor PM_{10} correlations found in recent human exposure studies were (for nonsmokers) approximately ~ 0.6–0.8. Thus, the monitor-to-monitor correlations of ambient PM concentrations at separate locations within a metropolitan area may be in the same order of magnitude as the person-to-monitor correlations. Therefore, an overall assessment of the link between personal exposure and the health effects of air pollution found in aggregate time-series studies need to take in to consideration both types of these variables.

In summary, the results from this study of nationwide air pollution data suggest that the apparent regional heterogeneity in PM effect estimates, as well as the differences in the significance of health outcome associations across pollutants, may in part be explained by the differences in monitor-to-monitor correlations by region and across pollutants. However, to achieve more comprehensive understanding of the link between personal exposure and ecologic level health effects in nationwide basis, more information is needed regarding the person-to-monitor correlation for a range of climate and locations. Also, more work is needed to develop a framework for designing of air quality network for epidemiological studies for both short-term and long-term health effects. Since such designs will need to consider the relative importance of local and regional pollution, the newly available data from the $PM_{2.5}$ chemical speciation network (U.S. EPA, 1997) should help evaluate their relative impacts, monitor representativeness, and redundancy.

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References

Chan C.C., and Hwang J.S. Site representativeness of urban air monitoring stations. *J Air Waste Manag Assoc* 1996: 46: 755–760.

Cleveland W.S. Robust locally-weighted regression and smoothing scatterplots. *J Am Statist Assoc* 1979: 74: 829–836.

Dominici F., McDermott A., Zeger S.L., and Samet J.M. On the use of generalized additive models in time-series studies of air pollution and health. *Am J Epidemiol* 2002: 156: 193–203.

Ebelt S.T., Petkau A.J., Vedal S., Fisher T.V., and Brauer M. Exposure of chronic obstructive pulmonary disease patients to particulate matter: relationships between personal and ambient air concentrations. *J Air Waste Manage Assoc* 2000: 50: 1081–1094.

Hastie T.J., and Tibshirani R.J. *Generalized Additive Models*. Chapman & Hall, New York, 1990.

Hwang J.S., and Chan C.C. Redundant measurements of urban air monitoring networks in air quality reporting. *J Air Waste Manag Assoc* 1997: 47: 614–619.

Insightful Corporation. 2001. S-Plus, Scattle, WA.

Ito K., Thurston G.D., Nadas A., and Lippmann M. Monitor-to-monitor temporal correlation of air pollution and weather variables in the North-Central US. *J Expos Anal Environ Epidemiol* 2001: 11: 21–32.

Janssen N.A., Hoek G., Brunekreef B., Harssema H., Mensink I., and Zuidhof A. Personal sampling of particles in adults: relation among personal, indoor, and outdoor air concentrations. *Am J Epidemiol* 1998: 147: 537–547.

Janssen N.A., Hoek G., Brunekreef B., Harssema H., and Brunkreef B. Personal exposures to fine particles in children correlates closely with ambient fine particles. *Arch Environ Health* 1999: 54: 95–101.

Krewski D., Burnett R.T., Goldberg M.S., Hoover K., Siemiatycki J., Jerrett M., and Abrahamowicz M. Reanalysis of the Harvard Six Cities Study and the American Cancer Society Study of Particulate Air Pollution and Mortality: Investigators Report, Part I: Replication and Validation; Part II: Sensitivity Analyses, Health Effect Institute, Boston, MA, 2000.

Lioy P.J., Waldman J.M., Buckley T., Butler J., and Pietarinen C. The personal, indoor, and outdoor concentration of PM10 measured in an industrial community during the winter. *Atmos Environ Part B* 1990: 24: 57–66.

Lippmann M., Ito K., Nadas A., and Burnett R. Association of particulate matter components with daily mortality and morbidity in urban populations. Health Effects Institute Research Report Number 95. Health Effects Institute, Cambridge, MA, 2000.

Mage D., Wilson W., Hasselblad V., and Grant L. Assessment of human exposure to ambient particulate matter. *J Air Waste Manage Assoc* 1999: 49: 1280–1291.

Samet J.M., Zeger S.L., Dominici F., Curriero F., Coursac I., Dockery D., Schwartz J., and Zanobetti A. The national morbidity, mortality, and air pollution study in the United States. Health Effects Institute Research Report Number 96 and 97. Health Effects Institute, Cambridge, MA, 2000.

Sarnat J.A., Koutrakis P., and Suh H.H. Assessing the relationship between personal particulate and gaseous exposures of senior citizens living in Baltimore, MD. *J Air Waste Manage Assoc* 2000: 50: 1184–1198.

Sarnat J.A., Schwartz J., Catalano P.J., and Suh H.H. Gaseous pollutants in particulate matter epidemiology: confounders or surrogates? *Environ Health Perspect* 2001: 109: 1053–1061.

Suh H.H., Koutrakis P., and Spengler J.D. The relationship between aerosol acidity and ammonia in indoor environments. *J Expos Anal Environ Epidem* 1994: 4: 1–22.

Tamura K., Ando M., Sagai M., and Matsumoto Y. Estimation of levels of personal exposure to suspended particulate matter and nitrogen dioxide in Tokyo. *Environ Sci (Tokyo)* 1996: 4: 37–51.

U.S. EPA National Office for Environmental Assessment Office of Research and Development Air Quality Criteria for Particulate Matter. EPA/600/P-95/001cF. Research Triangle Park, NC, 1996a.

U.S. EPA Office of Air Quality Planning and Standards. Review of the National Ambient Air Quality Standards for Particulate Matter: Policy Assessment of Scientific and Technical Information OAQPS Staff Paper. EPA-452\R-96-013. Research Triangle Park, NC, 1996b.

U.S. EPA Office of Air Programs Federal Air Quality Control Regions. Office of Air Programs Publications No. AP-102. Raleigh, NC, 1972.

U.S. EPA. National $PM_{2.5}$ Speciation Program: Overview, Objectives, Requirements, and Approach., 1997, Available from http://www.epa.gov/ttnamti1/pmspec.html.

Wallace L. Indoor particles: a review. *J Air Waste Manage Assoc* 1996: 46: 98–126.

Zeger S.L., Thomas D., Dominici F., Samet J.M., Schwartz J., Dockery D., and Cohen A. Exposure measurement error in time-series studies of air pollution: concepts and consequences. *Environ Health Perspect* 2000: 108: 419–426.