Combining PM$_{2.5}$ Component Data from Multiple Sources: Data Consistency and Characteristics Relevant to Epidemiological Analyses of Predicted Long-Term Exposures

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**Introduction**

Evidence of the association between long-term exposure to ambient PM$_{2.5}$ (particulate matter with diameter ≤ 2.5 μm) and human health continues to accumulate (Laden et al. 2006; Miller et al. 2007; Pope et al. 2002, 2004; Puett et al. 2009) and has spurred research into understanding the role of specific PM$_{2.5}$ chemical components (Mauderly and Chow 2006; Vedal et al. 2013). Recent cohort studies have relied on predictions of long-term average PM$_{2.5}$ concentrations at participant homes based on models developed from monitoring data (Eeftens et al. 2012; Paciorek et al. 2009; Sampson et al. 2011, 2013; Szpiro et al. 2010; Yanosky et al. 2009). A few additional studies have used this approach to estimate the health effects of PM$_{2.5}$ chemical components in the United States, most studies have used data from two networks: the U.S. Environmental Protection Agency (EPA) Chemical Speciation Network (CSN) and the Interagency Monitoring of Protected Visual Environments (IMPROVE). We performed exploratory analyses to examine features that could affect our approach to combining data: comprehensiveness of spatial coverage, comparability of analysis methods, and consistency in sampling protocols. In addition, we considered the viability of developing spatiotemporal prediction models given (a) all available data, (b) NPACT data only, and (c) NPACT data with temporal trends estimated from other pollutants.

**RESULTS:** The number of CSN/IMPROVE monitors was limited in all study areas. The different laboratory analysis methods and sampling protocols resulted in incompatible measurements between networks. Given these features we determined that it was preferable to develop our spatiotemporal models using only the NPACT data and under simplifying assumptions.

**CONCLUSIONS:** Investigators conducting epidemiological studies of long-term PM$_{2.5}$ components need to be mindful of the features of the monitoring data and incorporate this understanding into the design of their monitoring campaigns and the development of their exposure prediction models.

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discuss the spatial coverage of exposure monitoring, the filter analysis methods, and the sampling protocols. NPACT analyses focused on four primary pollutants: elemental and organic carbon (EC and OC), silicon, and sulfur as markers for combustion sources, crustal dust, and inorganic aerosol, respectively. Here we restrict our attention to EC and silicon, because these pollutants have been associated with adverse health outcomes (Ostro et al. 2010; Vedal et al. 2013) and they allow us to highlight similarities and differences in the features we compare.

**Methods**

**Population.** The NPACT study was based on the subjects who were originally recruited in MESA and consented to MESA Air or who were directly enrolled in MESA Air. The cohort includes approximately 7,000 participants residing in six U.S. metropolitan areas: Baltimore, Maryland; Chicago, Illinois; Los Angeles, California; Minneapolis–St. Paul, Minnesota; New York City, New York; and Winston-Salem, North Carolina (Bild et al. 2002; Kaufman et al. 2012).

**Data. NPACT monitoring data.** To characterize spatial variability of exposures across participant residences, the NPACT study expanded the MESA Air exposure assessment to include several NPACT outdoor sites that each provided one to three 2-week samples (average of 1.8 samples) from field activities and lab analyses. We compared pairs of daily average EC measurements for EC between the CSN and IMPROVE networks operated on different sampling schedules and used different sampling hardware. Whereas NPACT collected 2-week average samples, CSN/IMPROVE sites collected 24-hr average samples that were obtained every third day at all IMPROVE sites and at most core CSN sites, and every sixth day at supplemental CSN sites. The use of different sampling devices with different pump flow rates and blank correction methods may also contribute to data inconsistencies among monitoring networks.

**Exploratory data analysis for data comparability.** To assess data comparability between networks, we performed exploratory analyses by generating graphical displays (maps, scatter plots, and time-series plots) and summary statistics.

**Sparse coverage in urban space.** We investigated the potential impact of the number, density, and locations of monitors within each area on spatiotemporal prediction model estimates by assessing city-specific spatial distributions of monitors and comparing estimated temporal patterns between networks. The temporal patterns were estimated by smoothing time-series data across monitoring sites.

**Different filter analysis protocols.** We compared the two filter analysis methods for EC between the CSN and IMPROVE networks as well as within the CSN network. We compared pairs of daily average EC measurements collected from January 2000 through July 2007 at four co-located CSN and IMPROVE sites using the NIOSH TOT and IMPROVE_A TOR method.
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IMPROVE_A TOR filter analysis methods, respectively. In addition, there were 2 months of overlap from early May to early July in 2007 when both NIOSH TOT and IMPROVE_A TOR methods were used at the same core CSN sites. We compared pairs of daily average EC measurements during the overlapping time period using two methods at the six core CSN sites co-located with NPACT fixed sites.

Different sampling protocols. Given that NPACT collected 2-week average measurements and CSN and IMPROVE collected 24-hr samples every third or sixth day, it was not clear whether CSN and IMPROVE data could reliably estimate 2-week averages and temporal trends. The majority of CSN and IMPROVE data available for NPACT were measurements taken every sixth day at supplemental CSN sites. There were relatively few network sites with data collected every third day within 200 km of a MESA city center, because there were only 54 core CSN sites in the United States, and IMPROVE sites are mostly distant from cities. Thus we investigated the importance of sampling frequency by making within-site comparisons at four of the six CSN sites co-located with NPACT fixed sites that collected data every third day. Specifically, we compared the smoothed temporal patterns of 2-week average silicon estimates using data obtained from every third-day samples versus a reduced subset of every sixth-day samples. In addition to different sampling frequencies, the impact of differences in sampling hardware systems was compared at all six co-located sites using pairs of 2-week averages for EC and silicon from CSN and NPACT. The comparison for EC was restricted to the period during and after May 2007 when the IMPROVE_A TOR filter analysis method was adopted at core CSN sites. All six CSN sites co-located with NPACT fixed sites were core sites.

Exposure prediction model. The NPACT exposure prediction model aimed to predict 2-week average concentrations of PM_{2.5} components at participant addresses by adopting the spatiotemporal modeling framework developed for the MESA Air study. Overall, NPACT monitoring sites provided reasonable spatial coverage of MESA cities (average of 3–10 sites/km² for fixed and home-outdoor sites combined in each city). However, there were only three to seven fixed NPACT sites providing continuously collected data for each city (over 4 years for silicon or 18 months for EC), in contrast with the larger numbers of home-outdoor sites (87–116 per city) operating for only one to three 2-week periods. See Supplemental Material, Figure S1, for an illustration of the spatial and temporal resolution of the NPACT monitoring design in the Los Angeles area as an example. The spatiotemporal model was designed to effectively utilize such highly imbalanced monitoring data. Applications of the city-specific spatio-temporal models for PM_{2.5}, nitrogen dioxide (NO₂), nitrogen oxides (NOₓ), and black carbon in MESA Air have been described previously (Keller et al. 2015; Lindström et al. 2013b; Sampson et al. 2011; Szpiro et al. 2011) in situations where regulatory monitoring data were used to supplement the MESA Air campaign. The long time series of the regulatory monitoring data contributed to characterization of temporal features, whereas the MESA Air monitoring data enhanced the model at a relatively fine spatial scale. The model is available for implementation in the R package “SpatioTemporal” (Lindström et al. 2013a, 2013b). In brief, this model assumes that 2-week average space-time concentrations consist of site-specific long-term means, site-specific temporal trends, and spatiotemporal residuals. Long-term means and temporal trends vary over space as characterized by geographical predictors and spatial correlation structures. Temporal trends include spatially homogenous temporal trend functions scaled by spatially varying trend coefficients. Temporal trend functions are derived from a singular value decomposition of the data at sites with long time series before model fitting. Spatiotemporal residuals are assumed to be temporally independent but spatially dependent.

Exploration of possible spatiotemporal modeling approaches. We explored the possibility of fitting three approaches to develop city-specific spatiotemporal prediction models for silicon and EC based on our experience developing the MESA Air spatiotemporal model for PM_{2.5} (Keller et al. 2015). For this exploration, we used results of descriptive analyses described in the previous section (“Exploratory data analysis for data comparability”) and performed additional data analyses. First, we considered the full spatiotemporal model directly using all available PM_{2.5} component data from the regulatory and NPACT monitoring networks as in Keller et al. (2015) (Approach 1). In the PM_{2.5} spatiotemporal modeling work, the regulatory and MESA Air data were highly correlated and thus combined, allowing this rich data set to be used for the full model. The spatial density of PM_{2.5} component regulatory monitoring sites and the data comparability between networks are the criteria we considered to indicate the feasibility of Approach 1. In the event that the multiple sources of PM_{2.5} component data were insufficiently compatible to combine, NPACT data alone were too limited to support the full spatiotemporal model. To deal with such a case, we considered Approach 2 as a simplified version of the spatiotemporal model based only on NPACT data that assumed one temporal trend and without any spatial dependence structure. One homogeneous temporal trend in each city is a strong assumption. We investigated whether this assumption was appropriate by comparing a single temporal pattern estimated using fixed-site data for 4 years or 18 months with time-series data across about 50 home-outdoor sites in each city. Finally, we considered using the temporal trend functions estimated from other pollutant time series, such as PM_{2.5} and NOₓ, instead of those from PM_{2.5} components in the full spatiotemporal model framework (Approach 3). These pollutants have longer time series of data at many more regulatory monitoring sites than those of PM_{2.5} components in NPACT. Fitting the full spatiotemporal models using substituted trend functions in Approach 3 would be justified when there is good agreement between the two trend functions (i.e., the PM_{2.5}/NOₓ and the PM_{2.5} component trend functions). We compared the two temporal patterns between EC/silicon in NPACT and PM_{2.5}/NOₓ in the U.S. EPA AQS to assess the feasibility of Approach 3. Daily PM_{2.5} and NOₓ data measured at the U.S. EPA monitoring sites located within 200 km of the six MESA cities were obtained from the AQS database and converted to 2-week averages.

Results
Table 1 summarizes important characteristics of the PM_{2.5} component monitoring data across the NPACT, CSN, and IMPROVE networks. The table highlights three aspects of the regulatory and NPACT monitoring data that may make it difficult to combine the multiple sources in one unified spatiotemporal model: sparse spatial coverage, analysis method differences for carbon data, and different sampling protocols.

Data compatibility between CSN, IMPROVE, and NPACT networks. Sparse coverage in urban space. There were 6–27 CSN and 1–8 IMPROVE monitoring sites within 200 km of each city center (Figure 1 and Table 2). However, MESA participant homes were clustered near the center of each area, whereas only a few CSN sites were close to the city center and most IMPROVE sites were located in rural areas away from participants. See Supplemental Material, Figure S2, for estimated smoothed temporal patterns for the CSN and IMPROVE sites in six city areas. The temporal patterns for EC at eight IMPROVE sites were different from those observed at six CSN sites in Los Angeles. There were also differences between the temporal patterns for silicon across networks, but these were less striking. In the other five city regions, the temporal patterns for EC were more or less heterogeneous depending on city, whereas those for silicon were relatively consistent in all cities.
Different filter analysis protocols. Although Figure 2 shows that at four co-located sites there was moderate to high agreement between protocols (correlation coefficients = 0.79–0.91), these are not consistently and sufficiently high to conclude that the data are exchangeable in some city areas for daily average measurements of EC collected from the CSN versus IMPROVE networks before the method change in May 2007. See Supplemental Material, Figure S3, for a comparison of 24-hr average measurements of EC between the NIOSH TOT and IMPROVE_ATOR filter analysis methods for the 2-month period of overlap at one CSN site in each MESA city region. In Chicago and New York, the two methods had obvious systematic differences indicated by best-fit lines with negative intercepts, even though they were highly correlated; correlation coefficients were 0.94 and 0.97, attributable partly to the large variability between measurements in these cities. In contrast, the other cities displayed weaker systematic differences and had moderate correlations (0.71–0.84).

**Table 1.** Major contrasting characteristics among NPACT, CSN, and IMPROVE networks.

| Characteristic | NPACT | CSN | IMPROVE |
|---------------|-------|-----|---------|
| Sampling design | Urban | Urban | Rural |
| Location of sites | Dense (92–112 sites in each city) | Sparse (8–27) | Sparse (1–8) |
| Spatial density in MESA city areas | Dense (92–112 sites in each city) | Sparse (8–27) | Sparse (1–8) |
| Monitoring period | 2005–2009 | Since 1999 | Since 1987 |
| Sampling schedule | 2-week average | 24-hr average: 1 in 3 or 6 day | 24-hr average: 1 in 3 day |
| Filter analysis method | Analysis method for elements | XRF | XRF | IMPROVE_ATOR |
| Analysis method for carbon | NIOSH TOT | IMPROVE_ATOR | IMPROVE_ATOR |
| Blank correction using backup quartz filter | Yes | No | Yes |
| Sampling protocol | Sampler type for elements | HPEM | Met One SASS, Andersen RAAS, URG, R&P MASS, and URG 3000N | IMPROVE |
| Sampler type for carbon | HPEM | Met One SASS, Andersen RAAS, URG, R&P MASS, and URG 3000N | IMPROVE |
| Pump flow rate | 1.8 L/min | 6.7 – 16.7 L/min | 22.8 L/min |

Abbreviations: Andersen RAAS, Andersen Reference Ambient Air Sampler; HPEM, Harvard Personal Environmental Monitor; Met One SASS, Met One Speciation Air Sampler System; R&P, Rupprecht and Patahnick; URG, University Research Glassworks.

*XRF analysis was performed at Cooper Environmental Services of Portland, Oregon, and IMPROVE_ATOR analysis was performed at Sunset Laboratory Inc. of Tigard, Oregon. *New carbon sampling and analysis protocols have been implemented at core CSN sites since May 2007. *Used in about 75% of CSN sites in 2008.

**Different sampling protocols.** Table 2 indicates numbers of CSN and IMPROVE

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**Figure 1.** Locations of CSN, IMPROVE, and NPACT monitoring sites for PM$_{2.5}$ components within 200 km from city centers in six MESA city areas. Each map is restricted to a smaller area including all monitoring sites than the 200-km buffer area from the city center; one to three IMPROVE sites in four cities are not shown because they are hidden behind many other sites in the city center areas or with co-located CSN sites.
sites by sampling schedule. Fewer than half of the CSN sites (the core CSN sites) and all the IMPROVE sites sampled PM$_{2.5}$ components every third day, whereas more than half of the CSN sites (the supplemental sites) sampled every sixth day. Smoothed temporal patterns for 2-week averages of silicon based on CSN data collected at four sites co-located with NPACT fixed sites generally did not vary greatly when based on data collected every sixth day versus every third day at the same site, although a few local differences were evident (Figure 3). Correlations between 2-week average EC concentrations measured during May 2007–August 2008 at co-located NPACT fixed sites and CSN sites (using the IMPROVE_A TOR filter analysis method) in each city were relatively low (0.27–0.62) (Figure 4). In addition to NPACT measurements being generally higher than CSN measurements in all cities, there were nonsystematic differences indicated by some measurements being far from best-fit lines between the two networks. Time-series plots with smoothed temporal patterns of the same data used in Figure 4 show local differences over time (see also Supplemental Material, Figure S4). Supplemental Material, Figures S5 and S6, show that silicon measurements are more comparable than EC with higher correlation coefficients of 0.56–0.78.

Possible exposure modeling approaches. Approach 1: Full spatiotemporal models combining the CSN/IMPROVE and NPACT data. The regulatory monitoring data for PM$_{2.5}$ components in each city region within a 200-km boundary (7–32 sites) were more limited than those for other pollutants such as PM$_{2.5}$ in the much smaller area within 75 km of the city center (16–45 sites) (Table 2; see also Supplemental Material, Table S1). The descriptive analyses in the previous section (“Data compatibility between CSN, IMPROVE, and NPACT networks”) showed evidence of differences related to filter analysis methods and sampling protocols (Figures 2 and 4; see also Supplemental Material, Figures S4–S6). Thus, we concluded that NPACT data should not be combined with CSN and IMPROVE data to generate full spatiotemporal models for PM$_{2.5}$ components for each city.

Approach 2: Simplified spatiotemporal models based on the NPACT data only. Based on a graphical analysis comparing the single temporal pattern from NPACT fixed site data with measurements from the home-outdoor sites in each city (as illustrated for Los Angeles and Chicago in Supplemental Material, Figure S7), we concluded that the single smoothed temporal patterns generally represented the temporal variability across home sites.

Approach 3: Full spatiotemporal models using another pollutant. From the comparison of estimated temporal patterns for PM$_{2.5}$ and NO$_x$ based on U.S. EPA site data with those for EC and silicon based on fixed site NPACT data, we concluded that the patterns did not tend to be consistent enough to support using other pollutant data to generate full spatiotemporal models for PM$_{2.5}$ components (i.e., Approach 3). For example, temporal patterns for EC and silicon differed from those for PM$_{2.5}$ and NO$_x$ particularly in the Minneapolis and St. Paul area (see Supplemental Material, Figure S8).

Discussion

We explored the features of regulatory and NPACT monitoring data for EC and silicon relevant to our goal of combining all

Table 2. Number of sites with long-term monitoring data available within 200 km of six MESA city areas between 1999 and 2009.

| Area       | Total$^a$ | Regulatory CSN total | Regulatory CSN 3-day | Regulatory CSN 6-day | Regulatory IMPROVE$^b$ total (3-day) | NPACT fixed total (14-day avg) | NPACT home-outdoor total (14-day avg) |
|------------|-----------|----------------------|----------------------|----------------------|--------------------------------------|------------------------------|--------------------------------------|
| Los Angeles| 21 (137)  | 6                    | 3                    | 3                    | 8                                    | 7                           | 116                                  |
| Chicago    | 23 (122)  | 15                   | 4                    | 11                   | 1                                    | 7                           | 99                                   |
| Minneapolis–St. Paul | 10 (114)  | 6                    | 2                    | 4                    | 1                                    | 3                           | 104                                  |
| Baltimore | 37 (124)  | 27                   | 8                    | 19                   | 5                                    | 5                           | 87                                   |
| New York  | 31 (138)  | 25                   | 14                   | 11                   | 3                                    | 3                           | 107                                  |
| Winston-Salem | 19 (111)  | 12                   | 2                    | 10                   | 3                                    | 4                           | 92                                   |

$^a$Co-located sites are counted as multiple sites (two for CSN and NPACT or CSN and IMPROVE, and three for CSN, IMPROVE, and NPACT). $^b$The numbers of IMPROVE sites shown in Figure 1 are 7, 0, 1, 2, 2, and 3. One to three IMPROVE sites in four cities are not shown in Figure 2 because they are hidden behind many other sites in the city center areas or at sites co-located with CSN sites. $^c$Number of sites excluding NPACT–MESA Air home sites (number of sites including home sites). $^d$Thirteen sites appear in both Baltimore and New York due to overlap of regions: 12 CSN (for every-3rd-day and 9 for every-6th-day sampling sites, respectively) and 1 IMPROVE.
Figure 3. Time-series plots of log-transformed (Ln) 2-week averages of silicon between every-3rd-day and every-6th-day measurements at the same four CSN sites co-located with four NPACT fixed sites in Chicago, Minneapolis–St. Paul, Baltimore, and New York from 1999 to 2009.

Figure 4. Scatter plots of log-transformed 2-week averages of EC (μg/m²) for the overlapping period from May 2007 through August 2008 between co-located CSN and NPACT fixed sites in each of six MESA city areas.
available exposure data in spatiotemporal prediction models to investigate health effects of long-term exposures to PM$_{2.5}$ chemical components in the NPACT study. The small number of CSN and IMPROVE regulatory monitoring sites deployed in NPACT study areas limited the amount of additional data available for modeling. In addition, we found insufficient-between-network consistency to combine CSN, IMPROVE, and NPACT data in one spatiotemporal model. These findings led us to conclude that we should develop spatiotemporal models using NPACT monitoring data only. Given the limited space–time data in NPACT, the resulting spatiotemporal models needed to be simplified by assuming only a single temporal trend in each study area.

We found inconsistencies between measurements from the NPACT and regulatory monitoring networks for both EC and OC, even when both networks used the same filter analysis methods. Exploration of possible factors resulting in the inconsistency will help future studies that perform study-specific monitoring campaigns for PM$_{2.5}$ components to supplement regulatory data for exposure prediction and subsequent health analysis. For EC, we believe that the inconsistency is attributable primarily to differences in sampling periods of 2-week versus daily samples in NPACT and CSN/IMPROVE, respectively (see Supplemental Material, “Sampling periods and EC measurements,” for detailed information). In addition to the sampling period, other differences in carbon sampling between the networks could have contributed to inconsistencies in the data. NPACT used a blank correction protocol based on backup quartz filters, whereas CSN did not apply blank corrections. Filter handling, transport, and storage in NPACT may also have introduced artifacts and resulted in differences in measurements between the two networks, despite our extensive quality assurance and control procedures. However, the agreement between total carbon measurements in the CSN and NPACT networks (Vedal et al. 2013) suggests that the inconsistency of EC and OC measures between the two networks is more likely driven by the EC–OC split rather than the sampling and blank correction protocols.

Differences between silicon measurements from co-located NPACT and CSN monitors placed a few meters away from each other might be driven by microscale local plume gradients. Another possible explanation could be the use of different sampling equipment. Contamination of the filters by the silicon grease used in the HPEM sampler can result in increased silicon concentrations. However, grease contamination usually appears as very large spikes in contaminated samples compared with other samples; such spikes were not observed in our data (data not shown). Consistency between PM$_{2.5}$ and sulfur concentrations measured by the co-located monitors (data not shown) suggest that the Teflon filters used by the two networks generally sampled the same fine particles.

Some studies have developed calibration models to allow combined analysis of data collected by CSN and IMPROVE networks. White (2008) and Malm et al. (2011) used elemental, organic, and total carbon data in 2005 and 2006 at 7–12 co-located urban CSN and IMPROVE sites over the continental United States to estimate relationships of EC between the two networks. Their IMPROVE-adjusted EC at CSN sites was highly correlated with EC at co-located IMPROVE sites ($R^2 = 0.80–0.94$). However, these calibrations were based on data collected at a relatively small number of co-located sites during a short time period. More research is needed to determine whether these calibrations can be applied to other areas or years.

Unlike our study, other published studies of the health effects of long-term average PM$_{2.5}$ component concentrations have relied exclusively on regulatory monitoring data. Ostro et al. (2010) used CSN data and assigned PM$_{2.5}$ components at the nearest monitors to participant homes in California. Bergen et al. (2013) used CSN and IMPROVE data to build universal kriging models across the United States. Both studies used long-term averages and developed purely spatial models in large spatial domains. To take advantage of the extensive project-based monitoring campaigns designed to represent fine-scale spatial variability of PM$_{2.5}$ component concentrations across the target cohort residences, the NPACT options were either to use the NPACT data alone or to combine the NPACT data with regulatory monitoring data.

Our findings suggest that it may be difficult to transfer existing spatiotemporal prediction modeling approaches developed for PM$_{2.5}$ (Keller et al. 2015; Paciorek et al. 2009; Sampson et al. 2011; Yanosky et al. 2009) to modeling PM$_{2.5}$ components. Several features of the PM$_{2.5}$ component data make a direct transfer difficult. Although the regulatory PM$_{2.5}$ monitoring data were collected under consistent protocols over a relatively long period since the 1990s and across about 1,000 monitoring locations in the United States (Hand et al. 2011; U.S. EPA 2004), this is not the case for PM$_{2.5}$ component data. Furthermore, there is reasonable agreement for PM$_{2.5}$, unlike for PM$_{2.5}$ components, between these regulatory monitoring data and the data collected by community-based campaigns such as MESA Air (correlation coefficients $= 0.77–0.96$ at six co-located sites in six MESA city regions; data not shown). Thus, although Keller et al. (2015) and Sampson et al. (2011) were able to combine regulatory and MESA Air monitoring data in city-specific spatiotemporal predictive models of PM$_{2.5}$, we were unable to take the same approach in NPACT. Instead, we used only the NPACT data in PM$_{2.5}$ component prediction modeling in order to avoid introducing heterogeneity and bias into our results.

Given widespread scientific interest in understanding the associations between long-term air pollution exposure and health for multiple pollutants, it is important that we also acquire sufficient understanding of monitoring data features, which may in turn affect exposure predictions and the resulting health effect estimates. Methodological research has shown that features of the underlying exposure surface, exposure assessment design, and approaches to exposure modeling may all affect health effect estimates (Gryparis et al. 2009; Kim et al. 2009; Spiro and Paciorek 2013; Spiro et al. 2011). This study adds monitoring data from multiple sources as another feature that could affect exposure modeling for inference about health effects.

Conclusions

U.S. regulatory monitoring data for PM$_{2.5}$ components measured at CSN and IMPROVE sites are a potentially rich data resource to be used alone or combined with project-based monitoring data for the study of health effects of PM$_{2.5}$ components. However, the sparse spatial coverage of these networks and differences across networks in the analysis and sampling protocols for some PM$_{2.5}$ components could lead to biased or imprecise findings in health analyses, particularly if the data from different sources are combined without careful consideration. Future studies of long-term average concentrations of PM$_{2.5}$ components and health need to assess exposure data characteristics before designing their own monitoring campaigns and developing exposure prediction models.

References

Bergen S, Shepard L, Sampson PD, Kim SY, Richards M, Vedal S, et al. 2013. A national prediction model for PM$_{2.5}$ component exposures and measurement error-corrected health effect inference. Environ Health Perspect 121:1017–1026; doi:10.1289/ehp.1206010.

Bild DE, Bluemke DA, Burke GL, Detrano R, Diez Roux AV, Folsom AR, et al. 2002. Multi-Ethnic Study of Atherosclerosis: objectives and design. Am J Epidemiol 156:871–881.

Chow JC, Watson JD, Crow D, Lowenthal DH, Merrifield T. 2001. Comparison of IMPROVE and NIOSH carbon measurements. Aerosol Sci Technol 34:23–34.

Cohen MA, Adar SD, Allen RW, Avol E, Curl CL, Gould T,
et al. 2008. Approach to estimating participant pollutant exposures in the Multi-Ethnic Study of Atherosclerosis and Air Pollution (MESA Air). Environ Sci Technol 43:4687–4693.
de Hoogh K, Wang M, Adam M, Badaloni C, Beelen R, Birk M, et al. 2013. Development of land use regression models for particle composition in twenty study areas in Europe. Environ Sci Technol 47:5778–5786.
Diggel PJ, Menezes R, Su TL. 2010. Geostatistical inference under preferential sampling. J R Stat Soc C Appl Stat 59:191–232.
Eeftens M, Beelen R, de Hoogh K, Bellander T, Diggle PJ, Menezes R, Su TL. 2010. Geostatistical inference under preferential sampling. J R Stat Soc C Appl Stat 59:191–232.
Keller JP, Olives C, Kim SY, Sheppard L, Sampson PD, Szpiro AA, Paciorekj C, Sheppard L. 2013. A regionalized spatio-temporal model for air pollution with spatial and spatio-temporal covariates. Environ Ecol Stat 21:411–433.
Lippmann M. 2008. Semi-continuous speciation analyses for ambient air particulate matter: an urgent need for health effect studies. J Exp Sci Environ Epidemiol 19:235–247.
Malm WC, Schichtel BA, Pitchford ML. 2011. Uncertainties in PM_{2.5} gravimetric and speciation measurements and what we can learn from them. J Air Waste Manag Assoc 61:1131–1149.
moulderj JL, Chow JC. 2008. Health effects of organic aerosols. Inhal Toxicol 20:347–353.
Miller KA, et al. 2013. Development of land use regression models for PM_{10}, PM_{2.5} absorbance, PM_{10} and PM_{2.5} in 20 European study areas; results of the ESCAPE project. Environ Sci Technol 46:11195–11205.
Gelfand AE, Sahu SK, Holland DM. 2012. On the effect of preferential sampling in spatial prediction. Environmetrics 23:565–578.
Gryparis A, Paciorekj C, Zeka A, Schwartz J, Coili BA. 2008. Measurement error caused by spatial misalignment in environmental epidemiology. Biostatistics 10:258–274.
Hand JL, Copeland SA, Day DE, Dillner AM, Indresan H, Malm WC, et al. 2011. Spatial and Seasonal Patterns and Temporal Variability of Haze and its Constituents in the United States: Report V. June. Available: http://vista.cira.colostate.edu/improve/publications/Reports/2011/PDF/cover_TOC.pdf [accessed 21 May 2015].
Kaufman JD, Adar SD, Allen RW, Barr RG, Budoff MJ, Burke GL, et al. 2012. Prospective study of particulate air pollution exposures, subclinical atherosclerosis, and clinical cardiovascular disease: the Multi-Ethnic Study of Atherosclerosis and Air Pollution (MESA Air). Am J Epidemiol 176:825–837.
Keller JP, Olives C, Kim SY, Sheppard L, Sampson PD, Szpiro AA, et al. 2013. A unified spatiotemporal modeling approach for predicting concentrations of multiple air pollutants in the Multi-Ethnic Study of Atherosclerosis and Air Pollution. Environ Health Perspect 118:363–369; doi:10.1289/ehp.1001181.
Paciorekj C, Yanosky JD, Puett RC, Laden F, Suh HH. 2009. Practical large-scale spatio-temporal modeling of particulate matter concentrations. Ann Stat 3:370–397.
 Pope CA III, Burnett RT, Thurston GD, Maldonado JM, Krewski D, Ito K, et al. 2002. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. JAMA 287:1132–1141.
Pope CA III, Burnett RT, Thurston GD, Maldonado JM, Krewski D, Ito K, et al. 2002. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. JAMA 287:1132–1141.
Paciorekj C, Yanosky JD, Puett RC, Laden F, Suh HH. 2009. Practical large-scale spatio-temporal modeling of particulate matter concentrations. Ann Stat 3:370–397.
Pope CA III, Burnett RT, Thurston GD, Maldonado JM, Krewski D, Ito K, et al. 2002. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. JAMA 287:1132–1141.
Pacijorek C, Yanosky JD, Puett RC, Laden F, Suh HH. 2009. Practical large-scale spatio-temporal modeling of particulate matter concentrations. Ann Stat 3:370–397.
Pope CA III, Burnett RT, Thurston GD, Maldonado JM, Krewski D, Ito K, et al. 2002. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. JAMA 287:1132–1141.
Rao V, Frank N, Rush A, Dimmick F. 2003. Chemical Speciation of PM_{2.5} in Urban and Rural Areas. National Air Quality and Emissions Trends Report. Available: http://www.epa.gov/air/airtrends/agtrnd03/pdfs/2_chemspecifcm25.pdf [accessed 21 May 2015].
Sampson PD, Richards M, Szpiro AA, Bergen S, Sheppard L, Larson TV, et al. 2013. A regionalized national universal kriging model using Partial Least Squares regression for estimating annual PM_{2.5} concentrations in epidemiology. Atmos Environ 75:383–392.
Sampson PD, Szpiro AA, Sheppard L, Lindstrom J, Kaufman JD. 2011. Pragmatic estimation of a spatio-temporal air quality model with irregular monitoring data. Atmos Environ 45:6593–6606.
Schlesinger RB. 2007. The health impact of common inorganic components of fine particulate matter (PM_{2.5}) in ambient air: a critical review. Inhal Toxicol 19:811–832.
Sampson PD, Sheppard L, Malm WC, et al. 2011. Spatial and Temporal Dependencies in Air Pollution Concentrations with Complex Spatio-Temporal Dependencies. Environmetrics 21:605–631.
U.S. EPA (U.S. Environmental Protection Agency). 1998. Guideline on Speciated Particulate Monitoring (Draft 3). Research Triangle Park, NC: Office of Air Quality Planning and Standards, U.S. EPA. Available: http://epa.gov/ttnamti1/files/ambient/pm25/spec/dirspec.pdf [accessed 21 May 2015].
U.S. EPA (U.S. Environmental Protection Agency). 2004. Air Quality Criteria for Particulate Matter: Volume 1. EPA 600/P-99/0022a-1f. Washington, DC: U.S. EPA.
U.S. EPA (U.S. Environmental Protection Agency). 2005a. EPA Needs to Direct More Attention, Efforts, and Funding to Enhance Its Speciation Monitoring Program for Measuring Fine Particulate Matter. 2005-P-00004. Washington, DC: Office of Inspector General, U.S. EPA. Available: http://www.epa.gov/ttnamti1/files/ambient/pm25/spec/oigreport2005.pdf [accessed 21 May 2015].
U.S. EPA (U.S. Environmental Protection Agency). 2005b. EPA’s Final Draft National Ambient Air Monitoring Strategy: An Advisory by the Ambient Air Monitoring And Methods Subcommittee of the EPA Clean Air Scientific Advisory Committee. EPA-SAB-CASAC-05-006. Washington, DC: U.S. EPA. Available: http://www.epa.gov/sab/pdf/casac-05-006.pdf [accessed 21 May 2015].
U.S. EPA (U.S. Environmental Protection Agency). 2006. Modification of Carbon Procedures in the Speciation Network: Overview and Frequently Asked Questions (FAQs). Available: http://www.epa.gov/ttn/amtic/files/ambient/pm25/spec/faq/carbon.pdf [accessed 21 May 2015].
Vedal S, Kim SY, Miller KA, Fox JR, Bergen S, Gould T, et al. 2013. NPACT epidemiologic study of components of fine particulate matter and cardiovascular disease in the MESA and WH-DOS cohorts. In: National Particle Component Toxicity (NPACT) Initiative Report on Cardiovascular Effects. Research Report 178. Boston, MA: Health Effects Institute. White WH. 2008. Interim approach for relating the two datasets: discussion and action plan development. Presented at the IMPROVE–CSN PM Monitoring Workshop, Davis, CA, 22–24 January 2008. Available: http://vista.cira.colostate.edu/improve/Publications/Workshops/Carbon_Jan2008/IMP-CSN_White.ppt [accessed 21 May 2015].
Yanosky JD, Paciorekj C, Suh HH. 2009. Predicting chronic fine and coarse particulate exposures using spatiotemporal models for the Northeastern and Midwestern United States. Environ Health Perspect 117:522–529; doi:10.1289/ehp.11692.