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ORIGINAL ARTICLE

Exposure prediction approaches used in air pollution epidemiology studies: Key findings and future recommendations

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Many epidemiologic studies of the health effects of exposure to ambient air pollution use measurements from central-site monitors as their exposure estimate. However, measurements from central-site monitors may lack the spatial and temporal resolution required to capture exposure variability in a study population, thus resulting in exposure error and biased estimates. Articles in this dedicated issue examine various approaches to predict or assign exposures to ambient pollutants. These methods include combining existing central-site pollution measurements with local- and/or regional-scale air quality models to create new or "hybrid" models for pollutant exposure estimates and using exposure models to account for factors such as infiltration of pollutants indoors and human activity patterns. Key findings from these articles are summarized to provide lessons learned and recommendations for additional research on improving exposure estimation approaches for future epidemiological studies. In summary, when compared with use of central-site monitoring data, the enhanced spatial resolution of air quality or exposure models can have an impact on resultant health effect estimates, especially for pollutants derived from local sources such as traffic (e.g., EC, CO, and NO_x). In addition, the optimal exposure estimation approach also depends upon the epidemiological study design. We recommend that future research develops pollutant-specific infiltration data (including for PM species) and improves existing data on human time-activity patterns and exposure to local source (e.g., traffic), in order to enhance human exposure modeling estimates. We also recommend comparing how various approaches to exposure estimation characterize relationships between multiple pollutants in time and space and investigating the impact of improved exposure estimates in chronic health studies.

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INTRODUCTION

Given the limited spatial coverage of air pollution data, air pollution epidemiologic studies largely rely on data from central-site monitors, such as those reported in the United States (U.S.) Environmental Protection Agency's (EPA's) Air Quality System (AQS), to characterize a population's exposure to ambient air pollutants (e.g., all people living within 10 miles of a monitoring station).[1–3] However, measurements from central-site monitors often do not adequately capture the spatial and temporal variability of pollutant concentrations, which may result in an underestimation of the variability in the study population exposures.[4–10] Similarly, central-site monitors do not account for exposures in different microenvironments (e.g., indoors and in-vehicle) where pollutant infiltration[11–13] and indoor sources[14–16] can substantially impact total exposures. Consequently, there is a potential for exposure error and a resulting bias (e.g., underestimation of relative risks) when solely depending on ambient monitors to characterize exposure.

Exposure error in a study of the health effects of exposure to air pollution typically falls into two categories: classical error and Berkson error. Classical error occurs when the average of many replicate measurements of exposure does not equal the true exposure.[17] For example, if ambient air pollutant measurements taken over a week long period in different seasons are used to represent the annual pollution level. Berkson error occurs when one measure of exposure is used as a proxy for the exposure of many subjects.[17] For example, using measurements from one central-site monitor to represent the exposure of all participants living within 10 km of the monitor. Under the classical error model, the health effect estimate is biased with the degree of attenuation increasing as the variance of the exposure error increases, whereas Berkson error results in unbiased estimates, but the error increases the variance of the coefficients resulting in wider confidence intervals.[18] In reality, exposure estimates in most air pollution epidemiological studies will include elements of both types of error, which can complicate the interpretation of results.[19,20]

A number of refined exposure assessment approaches have recently been developed and applied in the investigation of air pollution health effects. Many of the articles in this dedicated issue of JESEE were presented at a symposium focused on issues of air pollution exposure and health ("Estimating Air Pollution Exposures for Health Studies: Comparison and Evaluation of Prediction Approaches"), held at the October 2011 International Society of Exposure Science (ISES) annual conference in Baltimore, MD. These

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alternative exposure assessment approaches included using various models to estimate exposure to ambient outdoor pollution with a finer degree of spatial and/or temporal resolution, accounting for factors such as outdoor-to-indoor transport (infiltration) and time-activity patterns, or combining existing models to create new, "hybrid" models for exposure. Many of the studies included a comparison of exposure estimation techniques across multiple pollutants. The studies were all conducted with a goal of comparing various approaches for estimating exposure and assessing their impact in epidemiology studies. A brief description of these articles is provided in Table 1 of Özkaynak et al.[21] The shared goal for all of these refined approaches is to reduce exposure error and its resulting bias, in order to provide more power to detect potential epidemiologic associations of interest.

Although the use of more refined exposure estimates may lead to reductions in some forms of exposure error, it is possible that new errors may also be introduced leading to greater uncertainty in observed health effect associations.[20,22] Improvements provided by these more refined exposure estimation approaches will depend on factors such as the influence of infiltration and human activity patterns on the pollutant concentration, the spatial and temporal patterns of the pollutant of interest, and the epidemiological study design (i.e., time series or cross-sectional designs). This article summarizes the key findings from a collection of papers and discusses the lessons learned in using alternative exposure estimation approaches for epidemiological studies of the short-term health effects of exposure to ambient air pollution. We then provide suggestions for future work to further refine and extend these techniques.

KEY FINDINGS AND LESSONS LEARNED

A summary of the key findings and conclusions from exposure and epidemiological research articles on this topic can be found in Tables 1 and 2. A variety of approaches were used as alternative methods for exposure assessment, including the use of improved approaches for predicting residential air exchange rates (an important predictor of indoor air concentrations and thus exposure) and the use of air quality or exposure modeling to provide spatially and/or temporally refined exposure estimates. The approaches attempted to quantify exposure differences in the study population both within an urban area and between multiple

Table 1. Air pollution exposure studies: Summary of key findings and conclusions for air pollution exposure studies included in this issue.

	Pollutant(s) investigated	*Study location Spatial coverage Spatial resolution*	*Exposure estimation approach(es)*	*Key findings*	*Key conclusions*
Baxter et al.[25]	$PM_{2.5}$	New Jersey 7 cities Within 10 km of monitor & 22 ZIP codes	Ambient monitoring. SHEDS. [a]AER and MB outdoor-to-indoor transport models. Hybrid of (2) and (3).	Daily correlations between all exposure tiers were strong ($r > 0.94$). Exposure difference between monitoring areas appeared to be driven by AERs. Seasonal patterns for exposure estimates appeared to be due to variations in PM composition and time-activity patterns.	High correlations between exposure surrogates suggest that the temporal variability in $PM_{2.5}$ concentrations were adequately captured by the central-site monitor. Geographic heterogeneity in housing stock (AER) and demographics (activity patterns) result in heterogeneity in ambient $PM_{2.5}$ exposure both within and between cities that is not captured by the central-site monitor.
Dionisio, et al.[27]	$PM_{2.5}$ EC SO_4 O_3 NO_x CO	Atlanta, Georgia Atlanta metro area 169 ZIP codes	Ambient monitoring. Modeled regional background (statistical model). AERMOD modeling. Hybrid of (2) and (3). [b]Exposure modeling (APEX or SHEDS).	Hybrid and exposure model estimates exhibit high spatial variability for CO, NO_x, and EC but little spatial variability among ZIP codes for $PM_{2.5}$, SO_4, and O_3. Degree of temporal variability represented was similar across exposure metrics for all pollutants except NO_x. Daily correlations between hybrid and exposure model estimates were strong ($r > 0.82$) for all pollutants	The use of ambient monitoring as an exposure surrogate for CO, NO_x, and EC ignores spatial variability at the ZIP code level. When temporal variability of pollutants is of interest, the use of hybrid or exposure model estimates may yield similar results. Exposure models affect the magnitude and distribution of exposure compared with ambient monitoring, especially for local pollutants (CO, NO_x, EC).
Beevers et al.[26]	$PM_{2.5}$ PM_{10} NO_2 NO_x	London, UK City of London 20×20 m grid cells	Hybrid approach combining CMAQ-urban with the KCL urban model	NO_2 has large variations within 10's of meters of major roads. NO_x can range by factor of 6 between early morning minimum and rush hour maximum. $PM_{2.5}$ can double close to road sources. PM_{10} from brake wear is 8 times greater near major roads than at suburban background.	Emissons-dispersion models can predict air quality spatially, temporally, and by source category. Temporal changes in pollutant concentrations can be replicated by dispersion models, especially in the complex near-road environment. Dispersion model results agree well with measurements in London; source apportionment results are uncertain. Human travel patterns are highly complex and support the need for the development of hybrid models and sophisticated human exposure models.

Abbreviations: AER, air exchange rate; AERMOD, AMS/EPA regulatory model (atmospheric dispersion modeling system); APEX, air pollutants exposure model; CMAQ, community multiscale air quality model; MB, mass balance; SHEDS, stochastic human exposure and dose simulation model.
[a]Lawrence Berkeley National Laboratory (LBNL) Aerosol Penetration and Persistence (APP) and Infiltration Models. [b]Both APEX and SHEDS used local, spatially varying air exchange rates as input. SHEDS was used for modeling $PM_{2.5}$, EC, SO_4, and O_3; APEX was used for modeling NO_x and CO.

urban areas. The exposure estimates obtained had varying influences on the health effect estimates when used in corresponding health studies. The health studies employed a variety of analysis methods, including case-crossover, case-control, and time-series epidemiologic studies and Bayesian analysis, to examine associations between air pollution and respiratory and/or cardiovascular morbidity.

Influence Air Exchange Rates and Human Activity Patterns

Individuals spend the majority of their time indoors,[23] yet the use of an ambient pollutant measurement from an outdoor monitor to approximate exposure is still the most common exposure surrogate. Each individual's exposure is likely to be different based on their time-activity behaviors and home characteristics.[24] Exposure models can provide insight into the between-individual variability of exposure to ambient pollution not captured by the central-site monitor by incorporating demographic differences, time-activity patterns and air exchange rates (AERs).[25–28] As an example, AER is a contributor to home-to-home variations in infiltration of outdoor pollution to the indoor environment that can in turn influence the personal exposure to ambient concentration relationships. Higher AERs suggest higher exposures to ambient air pollution indoors. Modeled estimates of AER can vary both spatially and temporally based on meteorology and housing characteristics.[25,27] Personal activities such as commuting can also affect exposures. Ambient concentrations for pollutants such as CO, EC, and NO_x are higher close to roadways, thus the amount of time spent in traffic can be a major contributor to personal exposures for these pollutants.

Epidemiological results varied when human exposure models were used to obtain estimates of exposure. In Mannshardt et al.,[29] the investigators observed a reduction in the uncertainty associated with the health effect estimates when utilizing human exposure models with Hierarchical Bayesian methods. Other analyses did not observe a significant difference in health effect estimates when utilizing human exposure models compared with air quality models[30] or compared with ambient monitoring data.[28,31] In addition to examining human exposure models, which incorporate a variety of human exposure factors, the effect of AER alone was analyzed. When used as an effect modifier, AER (or the exposure-concentration ratio, another surrogate for infiltration) significantly changed the health effect estimates of some pollutants ($PM_{2.5}$, O_3, NO_x, and CO). Higher health effect estimates were observed for some pollutants when AERs (or the exposure-concentration ratios) were higher.[28,31,32] These results suggest that accounting for a single well-characterized exposure factor such as AER may help to identify exposure variability in a population that is not typically accounted for with current exposure estimation techniques and point to the importance of incorporating exposure factors in exposure estimation approaches for air pollution epidemiology.

Spatial and Temporal Variability

The various air quality models applied appeared to increase the spatiotemporal variability of ambient concentrations of pollutants compared with the use of central-site monitoring data alone, especially for pollutants produced by local sources (i.e., EC, NO_x, and CO).[26,27,29] For example, hybrid approaches (i.e., combining different modeling approaches) provided full spatiotemporal coverage of study areas as opposed to the limited point locations provided by the ambient monitoring network.[27,29,33] The improved spatial resolution of air quality models had noticeable impacts on some epidemiologic health effect estimates. For traffic-related pollutants (e.g., EC, CO, and NO_x), Sarnat et al.,[30] showed larger relative risks (RR) and/or narrower confidence intervals (CIs) using spatially refined, modeled, ambient concentrations compared with central-site monitoring. However, the epidemiological study results for regional pollutants (e.g., $PM_{2.5}$, O_3) were mixed, with some studies seeing significant changes in health associations and/or narrower CIs[29,33] when using spatiotemporally resolved air quality modeling output (e.g., AMS/EPA Regulatory Model [AERMOD]—an atmospheric dispersion modeling system, Community Multiscale Air Quality model [CMAQ]—a regional-scale multipollutant transport and transformation model, remote sensing) compared with using central-site monitor measurements, whereas others did not.[28,30,31]

Improved characterization of spatial variability using air quality models can also help to better examine air pollution and socioeconomic status (SES) relationships. Depending on the location of the monitors, the exposures of certain subpopulations may not be well represented by the central-site monitor, leading to differential exposure error. Sarnat et al.,[30] showed significant effect modification by socioeconomic status (SES) for CO, NO_x, $PM_{2.5}$, and EC using the more spatially refined exposure estimates (e.g., air quality models estimates) but not when using the central-monitoring data. Relative risks were higher for the low SES group compared with the high SES group. However, Jones et al.,[28] only observed significant effect modifications with age (for O_3) and ethnicity (for $PM_{2.5}$) using the central-site monitoring data and not with the exposure model estimates.

Characterization of spatiotemporal variability of ambient pollutant concentrations and related exposures may also be improved by utilizing remote sensing[33] and sophisticated air quality modeling techniques (i.e., CMAQ).[29] Satellites have daily global coverage and can be used to retrieve estimates of air quality at a given location and time in a cost-effective manner. Kumar et al.,[33] combined satellite data with the *in situ* data at central-monitoring sites to develop robust estimates of daily exposure to $PM_{2.5}$ at any given location. Dionisio et al.,[27] found that the temporal variability may differ spatially across a metropolitan area when utilizing estimates combining regional background and dispersion models. For example, the temporal pattern of daily elemental carbon (EC) in the city center may be highly variable (likely due to traffic patterns), although there may be less temporal variability outside of the city center where traffic volume is lower. However, it is important to note that, in the studies summarized here, the mean temporal variability for most pollutants was adequately captured by the ambient monitor.[25,27]

Study Design

In studies of the health effects of exposure to ambient air pollution, the type of epidemiologic study design has important implications for the study results and their interpretation.[28–31] Case-crossover and time-series studies take advantage of temporal contrasts in exposures. Because of the above findings regarding temporal variability, the use of refined exposure estimation approaches may have minimal effects when used in case-crossover and time-series studies, especially for regional pollutants (e.g., $PM_{2.5}$) that exhibited greater spatial homogeneity.[28,30,31] It is noteworthy, however, that Sarnat et al.,[30] observed modestly stronger associations with more refined exposure estimates for local pollutants in a time-series study, when both the exposure estimates and health outcome data were resolved at the ZIP code level in Atlanta.

The emphasis of the studies summarized here has been on the short-term health effects of exposure to ambient air pollution. Cohort-based exposure and health studies are driven by both temporal and spatial contrasts in exposures. Improvements in the spatial characterization of exposures may be desirable in these studies as ambient monitors may not adequately capture spatial variability[25–27,33] depending on the pollutant of interest (regional *vs* local) and household factors (e.g., AER). In addition, personal

Table 2. Air pollution epidemiology studies: Summary of key findings and conclusions for air pollution epidemiology studies included in this issue.

	Study design	*Pollutant(s) investigated Health outcome(s) Analysis year(s)*	*Study location Spatial coverage Spatial resolution*	*Exposure estimation approach(es)*	*[a]Health effect estimate(s)*	*Effect modification by:*	*Key conclusions*
N. Hodas et al., [31]	Case-crossover	$PM_{2.5}$ Transmural MI 2004-2006	New Jersey 7 cities Within 10 km of monitor & 89 ZIP codes	1) Ambient monitoring 2) SHEDS 3)[b]AER and MB outdoor-to-indoor transport models 4) Hybrid of (2) and (3)	[c]OR: 1.10 (1.01, 1.19) [c]OR: 1.10 (1.01, 1.20) [c]OR: 1.10 (1.01, 1.20) [c]OR: 1.11 (1.02, 1.20)	residential AER	1) Little to no difference in OR estimates or CI across exposure estimation approaches 2) Higher OR for homes within the highest tertile of AERs compared to homes in the lowest AER tertile
R.R. Jones et al., [28]		$PM_{2.5}$ O_3 Hospital admissions for respiratory morbidity 2001-2005	New York City 4 county area 2,106 census tracts	1) Ambient monitoring 2) SHEDS	[d]HR: 1.013 (0.999, 1.028) for O_3 [e]HR: 1.018 (1.002, 1.034) for $PM_{2.5}$ [d]HR: 1.013 (0.998, 1.029) for O_3 [e]HR: 1.018 (1.002, 1.034) for $PM_{2.5}$	exposure/ concentration ratio sociodemographic characteristics	1) Little to no difference in HR estimates or CIs using ambient monitoring or SHEDS exposure estimates 2) Some effect modification by socio-demographic characteristics with ambient monitoring but not with SHEDS estimates 3) HR higher in highest exposure/concentration tertile for both $PM_{2.5}$ and O_3
N. Kumar et al., [33]		$PM_{2.5}$ Hospital admissions for AECOPD 2007	Cleveland, Ohio Cleveland metro area 2.5 km x 2.5 km grid cells	Hybrid statistical approach combining AOD with ambient monitoring	[f]RR: 2.3% increased risk of AECOPD with unit increase in $PM_{2.5}$; 54% greater chance of AECOPD admission among exposed group ($PM_{2.5} > 15.4\ \mu g/m^3$)	--	1) More reliable estimates from hybrid approach combining satellite based AOD and *in-situ* measurements compared to ambient monitoring data 2) Local time-space Kriging minimizes prediction error and addresses the problems of non-stationary variance across space and time
S.E. Sarnat et al., [32]	Time-series	$PM_{2.5}$ EC SO_4 O_3 NO_x CO [g]Emergency department visits for RD, ASW, and CVD 1999-2002	Atlanta, Georgia Atlanta metro area 169 ZIP codes	1) Ambient monitoring 2) Modeled regional background 3) [h]AERMOD modeling 4) [h]Hybrid of (2) and (3) 5) [i]Exposure modeling (APEX or SHEDS)	[j]RR: 1.069 (1.038, 1.100) for O_3 [j]RR: 1.012 (0.996, 1.029) for $PM_{2.5}$ [j]RR: 1.001 (0.991, 1.010) for NO_x [j]RR: 1.055 (1.028, 1.083) for O_3 [j]RR: 1.017 (1.000, 1.034) for $PM_{2.5}$ [j]RR: 0.997 (0.986, 1.009) for NO_x [j]RR: 1.013 (1.003, 1.023) for $PM_{2.5}$ [j]RR: 1.010 (1.001, 1.018) for NO_x [j]RR: 1.023 (1.006, 1.039) for $PM_{2.5}$ [j]RR: 1.009 (0.999, 1.019) for NO_x [j]RR: 1.053 (1.026, 1.081) for O_3 [j]RR: 1.009 (0.992, 1.026) for $PM_{2.5}$ [j]RR: 1.014 (1.004, 1.024) for NO_x	SES (for CO, NO_x, $PM_{2.5}$, and EC only)	1) Modestly stronger associations (larger RR and/or narrower CI) especially for traffic-related pollutants, using hybrid estimates of ambient concentrations compared to ambient monitoring 2) Associations similar or slightly weaker when using SHEDS exposure model outputs compared to hybrid estimates 3) Associations for ASW with CO and NO_x modestly stronger using APEX exposure modeling estimates compared to hybrid estimates 4) Low SES groups had higher RRs than high SES groups when using more refined exposure estimates but not using ambient monitoring
J.A. Sarnat et al., [30]		$PM_{2.5}$ O_3 NO_x CO Emergency department visits for ASW 1999-2002	Atlanta, Georgia Atlanta metro area 186 ZIP codes	Hybrid of modeled regional background and AERMOD modeling	[k]RR: 1.018 (1.003, 1.033) for $PM_{2.5}$ [k]RR: 1.050 (1.024, 1.075) for O_3 [k]RR: 1.010 (1.000, 1.019) for NO_x [k]RR: 1.008 (1.000, 1.016) for CO	residential AER (for $PM_{2.5}$, NO_x, and CO only)	1) Larger associations for $PM_{2.5}$, NO_x, and CO in ZIP codes with higher AERs compared to lower AERs in stratified models 2) Interaction term models showed positive, significant or near-significant effect modification by AER for CO and NO_x RRs; interaction term for $PM_{2.5}$ was negative and significant
E. Mannshardt et al., [29]	Bayesian	$PM_{2.5}$ Hospital admissions for RD and CVD 2002-2006	New York City 3 county area county	1) Ambient monitoring 2) CMAQ 3) SHEDS	[l]RR: 1.018 (1.0008, 1.033) [l]RR: 1.023 (1.010, 1.033) [l]RR: 1.023 (1.014, 1.033)	--	1) RR estimates using CMAQ or SHEDS are similar in magnitude but have smaller credible intervals than those using ambient monitoring 2) Uncertainty is reduced by about half when using CMAQ or SHEDS compared to using ambient monitoring 3) SHEDS exhibits higher power for detecting an increase in RR compared to ambient monitoring or CMAQ

Abbreviations: AECOPD: Acute exacerbation of chronic obstructive pulmonary disease; AER: Air exchange rate; AERMOD: AMS/EPA Regulatory Model (atmospheric dispersion modeling system); AOD: Aerosol optical depth; APEX: Air Pollutants Exposure model; ASW: Asthma/wheeze; CI: Confidence interval; CMAQ: Community Multiscale Air Quality model; CVD: Cardiovascular disease; HR: Hazard ratio; IQR: Interquartile range; MB: Mass Balance; MI: Myocardial infarction; OR: Odds ratio; RD: Respiratory disease; RR: Relative risk; SES: Socioeconomic status; SHEDS: Stochastic Human Exposure and Dose Simulation model [a]Numbers in parentheses represent minimum and maximum of 95% CI. [b]Lawrence Berkeley National Laboratory (LBNL) Aerosol Penetration and Persistence (APP) and Infiltration Models [c]Relative odds of a transmural MI with an interquartile range increase in $PM_{2.5}$ exposure. [d]HR for respiratory hospitalizations per IQR increase in O_3 concentration. [e]HR for respiratory hospitalizations per IQR increase in $PM_{2.5}$ concentration. HR given is for 2 day lag, HRs for lags 0-1 and lags 3-4 were not significant. [f]RR given as a percent increased risk per unit increase in $PM_{2.5}$ exposure within 9 days and $\sim$5 km. [g]Results in table are presented for ASW, for selected pollutants. For the full suite of RRs, see S. Sarnat et al., [32]. [h]O_3 results are not presented for the AERMOD and Hybrid metrics because O_3 was not modeled with AERMOD. [i]Both APEX and SHEDS used local, spatially varying air exchange rates as input. SHEDS was used for modeling $PM_{2.5}$, EC, SO_4, and O_3; APEX was used for modeling NO_x and CO. [j]RR for ASW per IQR increase in pollutant concentration. [k]RR per IQR increase in pollutant concentration, for univariate pollutant models. RRs given are for the overall models, RRs for AER stratified models and AER interaction term models can be found in J. Sarnat et al., [32]. [l]RR per one standard deviation increase in $PM_{2.5}$ concentration.

exposure factors such as time-activity patterns (e.g., commuting) may lead to greater exposure error and bias of the health effect estimate obtained and in some cases may even mask a true association.

RECOMMENDATIONS FOR FUTURE WORK

We can draw from this collection of studies a number of lessons helpful in planning future research to improve exposure estimates for use in health studies. The epidemiological study designs and methodological considerations will determine whether exposure factors (e.g., infiltration and time-activity patterns) can potentially modify the health effect estimates. A number of the studies in this issue found that increases in infiltration, characterized by residential AER[31,32] or the ambient exposure-concentration ratio,[28] were a source of important effect modification in epidemiological studies of ambient air pollution health effects. Consequently, improvements in the current prediction methods of AER, through evaluation and refinement of existing tools, will be highly valuable. Epidemiological study designs and methodological considerations (in particular, case-crossover *vs* time series for short-term effects studies) can make a difference in our ability to estimate the role of infiltration on health effects.[28,30,31] Researchers should test alternative model specifications to ensure that the statistical methods employed do not diminish their ability to study or estimate the role of building infiltration and other inter-subject ambient exposure-related factors (as in the case of case-crossover studies).

In addition to AER, other factors related to both personal exposure and ambient pollution (e.g., pollutant-specific residential infiltration rates, and time spent on or near roadways) may also be effect modifiers in epidemiological studies of both local and regional pollutants.[26,30,34–36] As epidemiological studies begin to focus more on $PM_{2.5}$ components, relevant residential infiltration models must be developed to account for component-specific penetration efficiencies and decay rates. Efforts should also be made to refine current tools and information for modeling exposures to ambient pollutant species in key exposure microenvironments (e.g., outdoors near home, commuting microenvironments, and non-residential indoor environments). Recently developed light-weight global positioning system (GPS) sensors used for continuous time-location data collection can greatly improve upon the accuracy and spatiotemporal resolution of existing time-activity surveys (e.g., EPA's Consolidated Human Activity Database (CHAD) or the American Time Use Survey (ATUS)), which are integral to exposure models. The information from these sensors can be combined with personal monitoring data in order to evaluate and/or modify our current exposure models. More attention should also be given to examining potential confounding because of correlation between SES-related factors and predicted or measured AER values.[32]

Increased spatial variability of ambient pollution exposure estimates was observed using both air quality and exposure models, especially for gaseous pollutants and PM species derived from local sources. Focusing on improvements in traffic/road proximity factors and local source emissions, which differ in time and space, may provide additional information related to exposure variability, which is typically lost when average or population-level exposures (e.g., county or ZIP code level) are used. We anticipate that current monitoring systems and the aforementioned GPS-based sensor technologies could provide a range of new information that could help with refining exposure estimates. Further, combining existing and new techniques for exposure estimation has shown value. Promising approaches include combining CMAQ and AERMOD model results, or incorporating highly resolved satellite data[33] using a Hierarchical Bayesian framework to blend ambient concentrations, and housing and exposure-related information.[29]

Available health data typically have their own spatial or temporal limitations (e.g., hospital admissions by county *vs* ZIP code, or by month *vs* day). If exposure estimates can be produced at a fine spatiotemporal scale, these will only be useful if health data are also available on the same scale. It is necessary to determine the relative importance of spatial *vs* temporal resolution in both exposure estimates and health data specification, for various types of epidemiological study designs, in order to make best use of development efforts for new or highly resolved exposure estimates, as well as for the planning of future studies. In addition, combining exposure modeling and epidemiology with knowledge gained from toxicological studies can help our understanding of which pollutant or group of pollutants are likely to be linked with health effects.

Finally, two topics that were not addressed by the studies published in this issue were multipollutant relationships and the differences between acute and chronic studies. As epidemiological studies begin to incorporate multiple pollutants into their models, it is important to understand the relationships between the pollutants. These between-pollutant relationships may not be accurately characterized by the existing central-site monitors. Ambient pollutants can have different spatiotemporal patterns because of their sources, chemical/physical properties, and pollutant-specific interactions with meteorology, all of which may cause pollutant concentrations to not be correlated with each other. For example, a pollutant such as O_3 may be relatively homogeneous within an urban area, but the location of roads may greatly affect the spatial pattern of pollutants such as CO or NO_x. Because of this, the O_3-CO or NO_x relationships may be different depending on which exposure estimation approach (e.g., central-site monitors *vs* air quality models) is selected. Additional work is needed to better understand how the choice of exposure estimation approach affects the observed relationships between pollutants. Finally, studies examining longer exposure windows (e.g., 10 years or more) and related disease processes (e.g. cancer) were not adequately addressed by this collection of papers. Therefore, a systematic evaluation of the value of refined exposure characterization for both acute and chronic exposures, as they apply to related epidemiological studies, is of keen interest for advancing the knowledge base on air pollution exposures and associated health effects.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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DISCLAIMER

Although this work was reviewed by EPA and approved for publications, it may not necessarily reflect official Agency policy. The views expressed are those of the authors (s) and not necessarily those of the NHS, the NIHR or the Department of Health.

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