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Engaging academia to advance the science and practice of environmental public health tracking

Heather Strosnider[a,*], **Ying Zhou**[a], **Lina Balluz**[a], and **Judith Qualters**[b]

[a]Centers for Disease Control and Prevention, National Center for Environmental Health, Division of Environmental Hazards and Health Effects, Environmental Health Tracking Branch, 1600 Clifton Road, MS-F60, Atlanta, GA 30333, USA

[b]Centers for Disease Control and Prevention, National Center for Environmental Health, Division of Environmental Hazards and Health Effects, Office of the Director, 1600 Clifton Road, MS-F60, Atlanta, GA, 30333, USA

Abstract

Public health agencies at the federal, state, and local level are responsible for implementing actions and policies that address health problems related to environmental hazards. These actions and policies can be informed by integrating or linking data on health, exposure, hazards, and population. The mission of the Centers for Disease Control and Prevention's National Environmental Public Health Tracking Program (Tracking Program) is to provide information from a nationwide network of integrated health, environmental hazard, and exposure data that drives actions to improve the health of communities. The Tracking Program and federal, state, and local partners collect, integrate, analyze, and disseminate data and information to inform environmental public health actions. However, many challenges exist regarding the availability and quality of data, the application of appropriate methods and tools to link data, and the state of the science needed to link and analyze health and environmental data. The Tracking Program has collaborated with academia to address key challenges in these areas. The collaboration has improved our understanding of the uses and limitations of available data and methods, expanded the use of existing data and methods, and increased our knowledge about the connections between health and environment. Valuable working relationships have been forged in this process, and together we have identified opportunities and improvements for future collaborations to further advance the science and practice of environmental public health tracking.

Keywords

Environmental public health tracking; Surveillance; Air pollution; Drinking water; Environmental health

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*Corresponding author. Fax: +1 770 488 1538. HStrosnider@cdc.gov.
YZhou2@cdc.gov (Y. Zhou), LBalluz@cdc.gov (L. Balluz), JQualters@cdc.gov (J. Qualters).

1. Introduction: the mission

The prevention and mitigation of health problems related to biological, chemical, or physical hazards in the environment are important functions of public health (Thacker et al., 1996). Such functions are supported through surveillance, the ongoing systematic collection, analysis, and interpretation of outcome-specific data used to plan, implement, and evaluate public health practice (Buehler, 2012; Thacker and Berkelman 1988). In 2000, the Pew Commission identified gaps in environmental health data and information hindering these functions in the United States (Pew Commission, 2000). They described a lack of data for the leading causes of mortality and morbidity, a lack of data on exposure to hazards, a lack of environmental data with applicability to public health, and barriers to integrating and linking existing data. Without these data, public health agencies cannot fulfill their primary responsibility which includes implementing actions and policies that increase the information available to the public and decision makers, protect people from harm, promote health, and create environments that support healthy behaviors (Frieden, 2013).

The ability of public health agencies to implement data-driven actions and policies in environmental health would improve with (1) enhancements in methods and tools to better use existing data to track the association between health and environment for small areas over time; (2) an understanding of how the characteristics of the data and methodological decisions impact results; (3) advanced methods to address ecological bias, control for confounders and effect modifiers, and improve exposure characterization aimed at the gaps in available data; and (4) recommendations and techniques for improving the data collected including the identification of key missing data and data elements and creation standards for data collection and reporting (Elliott and Wartenberg, 2004; Jarup, 2004; Litt et al., 2004; Mather et al., 2004; Ritz et al., 2004). Continued improvements in the understanding of the relationship between the environment and health through epidemiologic and toxicological studies would help identify what should be tracked and how it should be tracked (Thacker et al., 1996). Further, better integrated research, surveillance, and practice would help address the challenges and needs of state and local public health agencies (Beale et al., 2008; Kyle et al., 2006).

Since 2002, the Centers for Disease Control and Prevention's (CDC) National Environmental Public Health Tracking Program (Tracking Program) has collaborated with state and local health departments, academic partners, other federal agencies, and non-government organizations (Fig. 1) to address the challenges identified by the Pew Commission and to implement a nationwide network of integrated health and environmental data that can drive actions to improve the health of communities. Environmental public health tracking combines traditional public health surveillance of health outcomes with the collection, integration, analysis, and dissemination of data from environmental hazards (chemical, biological, or physical) and population exposure monitoring (McGeehin et al., 2004). These data are linked, spatially and temporally, to detect and monitor trends in disease burden and the associations between health outcomes and hazards, provide information to the public, and evaluate our progress in protecting the public's health. These data linkage projects can also inform public health action and policy by identifying areas or populations at risk, highlighting sources of exposure to an environmental hazard, or demonstrating the contribution of environmental hazards to adverse health outcomes within the population. Such projects can facilitate the generation of hypotheses regarding etiology (Ritz et al., 2004). However, confirming etiology from data linkages is not easily achieved and often depends on the characteristics of the data and our current understanding of the relationship between the hazard, exposure, and health outcome under investigation.

2. Tracking: the early years

The Tracking Program initially collaborated with federal, state, local, and academic partners to identify priority environmental health issues, develop a vision and strategic plan, build partnerships, and conduct pilot linkage projects (Litt et al., 2004; Mather et al., 2004; McGeehin et al., 2004; Ritz et al., 2004). Together, we have identified data requirements, developed data standards, enhanced workforce capacity, and built the technical infrastructure to manage and disseminate data, analyses, and relevant public health information that we have synthesized (Bekkedal et al., 2008; Charleston et al., 2008; Li and Dawson, 2008; Love et al., 2008; Malecki et al., 2008; McGeehin, 2008; Patridge and Namulanda, 2008). That technical infrastructure is the National Environmental Public Health Tracking Network (Tracking Network), a Web-based, distributed surveillance system of secure and public portals at federal, state, and local levels (http://www.cdc.gov/nceh/tracking/). The Tracking Network contains standardized health, exposure, environmental, and population data and provides interactive tools for data exploration and visualization. Through its public portals, the Tracking Network disseminates county level data for many environmental health topics including air quality, contaminants in the community water system, childhood lead poisoning, birth defects, cancer, reproductive and birth outcomes, asthma, heart attacks, heat stress and carbon monoxide poisoning. In addition, more spatially and temporally resolved data has been integrated into the Tracking Network for use by Tracking Program's scientific experts at federal, state, and local levels.

Using the Tracking Program's data and technical infrastructure, we have collaborated to select, integrate, and analyze health, exposure, hazard, and population data to inform public health actions and policies in several key areas. Tracking Program partners have evaluated the association between ambient levels of ozone and $PM_{2.5}$ and traffic density with short-term asthma-related health outcomes (Babin et al., 2007; Paulu and Smith, 2008; Wilhelm et al., 2008). These analyses identified age- and sex- specific populations at risk as well as differences in the exacerbation of asthma-related outcomes particular to the exposure scenario. This information can be used to target public health interventions to manage asthma or to guide further investigations. Tracking Program partners in New York City have evaluated the effects of temperature and humidity on respiratory- and cardiovascular-related hospitalizations and contributed important information for local extreme heat response efforts (Lin et al., 2009). Tracking Program partners in New York State studied the short-term effects of air pollution on cardiovascular-related hospitalizations and identified sensitive sub-populations to which interventions should be targeted (Haley et al., 2009). In St. Louis, Tracking Program partners evaluated whether building demolition contributed to childhood blood-lead levels and informed policies for permitting demolition (Rabito et al., 2007).

The Tracking Program and its partners have developed and enhanced data and tools to address some of the challenges in the science and practice of environmental public health tracking. With the Imperial College of London, we have modified the Rapid Inquiry Facility (RIF), a tool for estimating health risk related to environmental hazards, to be compatible with the Tracking Program's technical infrastructure (Beale 2008). The Case-Crossover Analysis Tool (C-CAT) was developed to increase the usability of the case-crossover method (Talbot et al., 2009). We partnered with U.S. Geological Survey (USGS) to address gaps in domestic well-water data by summarizing data from two USGS databases (USGS 2007). In collaboration with the U.S. Environmental Protection Agency (EPA), we have developed a hierarchical Bayesian model to predict daily $PM_{2.5}$ concentrations on a small scale (Vaidyanathan et al., 2013). Further we have hosted several workshops with EPA, academia, and state and local partners to identify and collaborate on common methodological challenges (Matte et al., 2009; Ozkaynak et al., 2009) and have evaluated the use of different data sources and methods for tracking health outcomes, exposures, and hazards (Beale et al., 2010; Rabito et al., 2007; Talbot et al., 2009; Wartenberg et al., 2008; Wilhelm et al., 2008; Young et al., 2008).

3. Challenges remain

Through collaborations with our partners, we continue to better characterize and prioritize the challenges in data availability and quality, the methods for data integration and analysis, and the science we use to translate data into useful public health recommendations and actions. First our efforts continue to be hindered by the lack of relevant data to support the analyses we need to conduct. When data are available, key elements, such as resident address for health data or limit of detection for environmental data, may be missing, the spatial and temporal resolution between data may be insufficient or incompatible, or access to the data may be restricted. For example, Welhelm et al. (2008) incorporated many important confounders in their analysis of air pollution, traffic density, and asthma morbidity on a small spatial scale, but missing information about the child's school or day care location, time activity patterns, and housing filtration created the potential for exposure misclassification. In addition, the asthma related effects of air pollution or traffic may have been underestimated because only incidence of asthma outcomes among children previously diagnosed with asthma by a doctor was reported (Wilhelm et al., 2008). In another study, Babin et al. (2007) found that children aged 5 to 12 years were more susceptible to ozone and $PM_{2.5}$ in Washington, DC, but the low levels of air pollution, lack of spatial coverage by the air monitors, and restriction of health data to the ZIP code level made it difficult to identify any spatial patterns for ozone or $PM_{2.5}$ associations within the district.

Second, to link and analyze the data, we often have to rely on sophisticated methods for which we must evaluate their use for tracking, develop technical guidance to support their application, and enhance workforce capacity to use them (Mather et al., 2004). Tracking Program partners in Utah found a positive association between bladder cancer and the presence of EPA Toxics Release Inventory (TRI) sites through a case-control analysis comparing census tracts with high, stable bladder cancer rates and census tracts with neutral, stable cancer rates (Fortunato et al., 2011). It's unclear how modeling decisions, data characteristics, outcome sparseness, strength of association, and spatial autocorrelation may affect results of this and similar studies. Similarly, the case-crossover method is used frequently to analyze the effects of air pollution and heat, however, we need to understand the effects of decisions such as referent period selection and estimation of air pollution and meteorological conditions on study results (Paulu and Smith, 2008). Sophisticated modeling approaches for air pollution, such as kriging or land use-based regression modeling, better characterize spatial and temporal variability in air pollution (Jerrett et al., 2005; Wilhelm et al., 2008), however, they require expertise and resources that are not always available within a single institution or agency. In addition, both case-crossover and Poisson time series analyses can only estimate short term effects of air pollution and cannot be used to study and track the chronic effects and the combined acute and chronic effects of air pollution (Haley et al., 2009). More effort is needed in to evaluate and apply sophisticated methods that address environmental health priorities associated with air pollution as well as with hazards in other environmental media, such as groundwater and surface water used for drinking.

Lastly, to interpret the data linkages and translate them for public health practice a scientific understanding about the relationship between hazard, exposure, and health that is grounded in sound epidemiologic and toxicological studies is needed (Thacker et al., 1996). Further complicating efforts to track the associations between health and environment is the complex relationship between hazards, exposure, and health effects. People are exposed to multiple hazards in the environment in different physical settings and geographic locations throughout their lifetime, many non-environmental factors contribute to morbidity and mortality, and a long latency period can occur between the environmental exposure and the presentation of an adverse health effect. Addressing latency is complicated by exposures to hazards or contaminants that do not persist in the body, do not produce a unique or detectable biomarker, or do not “occur in a setting where there is a readily identifiable significant hazard”(Thacker et al., 1996). The Tracking Program must better connect with the research community to help decide not only what environment and health data should be tracked, but also how best to track them (Kyle et al., 2006; Pew Commission, 2000).

4. Continued collaboration with academia to address challenges

The methods and tools used in environmental public health tracking are similar to those used in environmental health research, though the two practices may differ in both the purpose for the analysis and the resolution of the data used. Both fields face similar challenges. By bringing together researchers and practitioners, we can better inform the research needed to support practitioners and enhance the skills of the environmental public health tracking workforce. In 2010, the Tracking Program initiated three year contracts with academia to further address the gaps and challenges in the science and practice of environmental public health tracking. The Tracking Program sought to fund activities that would expand and advance the methods, tools, and science needed for environmental public health tracking and enhance the understanding of environmental risk factors and their relationships with human health. Proposals were solicited under four topic areas; seven projects representing five educational institutions were funded (Table 1). The aim of each topic, results to date for each project, and the successes and challenges in these partnerships with educational institutions are outlined in the following subsections.

4.1. Topic 1: development of environmental epidemiologic and statistical methods for use on the tracking network

Topic 1 was aimed at developing analytic tools and methods that were supported by well-defined statistical principles and would provide environmental public health practitioners the ability to evaluate spatial and temporal relationships between selected environmental factors and health effects. The University of California, Berkeley (UCB) enhanced an existing multi-level analytic tool called GAMEPHIT to enable detection of unexpectedly high disease rates while controlling for variables likely to confound environmental health relationships. Most statistical methods assume independence between spatial units, such as census tracts or counties; however, spatial units closer to each other are more similar than units which are farther apart (spatial autocorrelation). The enhanced GAMEPHIT tool, now available to the Tracking Program and its partners, can estimate as many as three levels of random effects with an independence assumption or two levels with control for spatial autocorrelation.

UCB also explored methods for addressing data gaps by using surrogate information from other data sources such as national health surveys or traffic density. They developed highly resolved estimates of ambient concentrations of $PM_{2.5}$ using an air pollution model that combined a land-use regression model (LUR) with a machine-learning method and Bayesian Maximum Entropy interpolation of the LUR space-time residuals (Beckerman et al., 2013). In the conterminous United States, 1460 stations monitor the air for $PM_{2.5}$, however, the stations are mostly clustered in urban areas and do not adequately capture secondary $PM_{2.5}$ formed in the atmosphere (Jerrett et al., 2005). The team developed an air-pollution model that provides monthly estimates of $PM_{2.5}$ at the census-tract and ZIP-code levels. The team used 20 years of Behavioral Risk Factor Surveillance System (BRFSS) data, a machine-learning approach, and the GAMEPHIT tool to develop a model to estimate smoking and obesity prevalence (Ortega et al. submitted to journal). The team derived estimates of smoking and obesity prevalence at the census-tract and ZIP-code levels for four time periods between 1991 and 2010 by combining parameter estimates from the model with census data. These estimates help fill a data gap for key factors that confound the relationship between environmental hazards and health. They also evaluated applying an indirect adjustment method for multiple missing variables using ancillary data, such as national health surveys, to environmental epidemiology (Shin et al. 2014). They found that when the ancillary data are representative of the study population, such methods are useful for addressing missing covariates and reducing bias.

4.2. Topic 2: development of environmental exposure assessment methods for use on the tracking network

Topic 2 was intended to promote using available environmental hazard and biomonitoring data to characterize population exposure to environmental contaminants. The University of Pittsburgh (PITT) evaluated methods to assess the effects of lead in ambient air on the blood-lead levels of children. Using ecologic and individual level study designs, the PITT team evaluated using lead emissions data to identify children at risk for elevated blood lead levels. Results of a county-level analysis showed concentrations of lead in air estimated by US EPA's National Air Toxics Assessment (NATA) were correlated significantly with the percentage of children tested who had blood-lead levels greater than or equal to ten micrograms per deciliter, that even after controlling for percent older housing and poverty (Brink et al., 2013). However, in comparing the NATA data to EPA's ambient air lead monitors, they found that the NATA data underestimated lead in the air. While the highest quartile of the NATA data correlated well with the lead monitoring data, the lower quartiles did not. For an individual level analysis, PITT is using proximity to a lead-emitting TRI site as the exposure variable. In Kansas, they found that children's blood-lead levels decreased as proximity to a lead-emitting TRI site decreased but not as proximity to a toluene emitting sites decreased, again even after controlling for pre-1950 housing and poverty levels. The PITT team is conducting similar analyses for Missouri, New Jersey, New Mexico, and Pennsylvania. Additional analysis evaluating the association between ambient air lead, blood lead, home dust lead, and other factors using the National Health and Nutrition Examination Survey (NHANES) data is also underway.

4.3. Topic 3: linkage study of air quality PM and health effects data from the tracking network

The Tracking Program funded three academic partners, UCB, PITT, and the University of Medicine and Dentistry of New Jersey (UMDNJ), to address Topic 3, which proposed increasing the use of data from the Tracking Network to track the effects of $PM_{2.5}$ exposure associated with health outcomes. Topic 3 also called for academic partners to evaluate current literature on $PM_{2.5}$ and health, to make recommendations for additional measures most appropriate for characterizing the health effect of exposure to $PM_{2.5}$, and to evaluate the application of biomarkers of exposure and of effects of $PM_{2.5}$ for the Tracking Network.

UCB is evaluating methods to track the effects of air pollution on cardiovascular health and is supporting the implementation of those methods within state and local health departments. They are conducting a case-crossover analysis linking modeled $PM_{2.5}$ concentrations, hospital admissions for acute myocardial infarction (AMI), congestive heart failure and stroke, and effect modifiers and confounders such as income, race/ethnicity, smoking, and obesity. Unfortunately, limited data exist for important effect modifiers and confounders for conducting such linkage studies. Once the analysis is complete, UCB will conduct a sensitivity analysis and investigate the contribution of effect modifiers and confounders to the spatial variation in the association between $PM_{2.5}$ and cardiovascular health. This work will expand our understanding of the effect of existing data limitations on linkage studies and identify key covariates for tracking the health effects of $PM_{2.5}$. UCB is working closely with state and local health departments and is providing them statistical analysis code and exposure assignments as well as modeled census tract-level smoking and obesity prevalence data developed by a separate UCB research team working on Topic one, as described earlier in this paper.

UCB is conducting two studies to explore using biomarkers of exposure to $PM_{2.5}$ and biomarkers of effect for cardiovascular disease for tracking $PM_{2.5}$ exposure and its effects on cardiovascular health. During the first study, the team will assess the association between $PM_{2.5}$ exposure and inflammation biomarkers in the CVD pathway using NHANES data. During the second study, they will evaluate the association between urinary polycyclic aromatic hydrocarbons measured in NHANES participants, potential exposure using information on food intake and indoor air from the NHANES questionnaire, and $PM_{2.5}$ estimates from modeled data. Both projects will use Hierarchical-Bayesian $PM_{2.5}$ estimates developed by EPA with the Tracking Program.

PITT is also evaluating methods to track the effects of air pollution on cardiovascular health and supporting implementing those methods within state and local health departments. They have conducted a descriptive analysis of temporal trends, spatial variation, and gender differences in age-adjusted rates of hospitalizations for AMI using data currently available on the Tracking Network (Talbott et al., 2013). Results showed a 20% decrease in AMI hospitalizations from 2000 to 2008 for most Tracking states, higher rates in the New England/Mid-Atlantic region, and two-fold higher rates among men than women. They also conducted a case crossover analysis using individual level data for hospitalizations related to the circulatory system and modeled $PM_{2.5}$ data from Florida, Massachusetts, New Hampshire, New Jersey, New Mexico, New York, and Washington (Talbott et al., 2014). Results showed a significant association between low levels of $PM_{2.5}$ and hospitalizations for illnesses related to various circulatory systems, including ischemic heart disease, congestive heart failure (CHF), AMI, cardiac arrhythmia, cerebrovascular disease (stroke), and peripheral vascular disease (PVD), year-round in some states but only cooler months in others. PITT has reviewed the literature to develop recommendations for additional cardiovascular measures for the Tracking Network. They recommend including measures of mortality, hospitalizations, and emergency department visits for CHF and mortality for stroke, but exclude measures for cardiac arrhythmia and PVD because the results from published studies on these latter measures are inconsistent. They also noted that read-mission for CHF is common and should be addressed when tracking CHF hospitalizations. Pitt also is investigating the link between measures of effect for CVD and $PM_{2.5}$ using NHANES data.

UMDNJ is evaluating the effects of data limitations and methodologic decisions for linking air pollution and birth outcomes. An initial evaluation using modeled $PM_{2.5}$ data highlighted variability among states in the association between total $PM_{2.5}$ and specific adverse birth outcomes at the county level (Harris et al. 2014, in press). Regional differences in specific components of $PM_{2.5}$ could cause such variability. They also investigated the effects of different spatial resolutions of the $PM_{2.5}$ data and found diminished associations when using finer spatial resolution in the analysis. One explanation for this discrepancy could be that the larger geographic scale captures and describes exposure more accurately as people typically do not stay at home during the day. Additional analysis will evaluate the association between specific components of $PM_{2.5}$ and adverse birth outcomes using individual level data.

4.4. Topic 4: linkage study of exposure data from safe drinking water information system (SDWIS) and health outcome data from the tracking network

Topic 4 projects were designed to increase the use of drinking water data to investigate the association between specific drinking water contaminants and adverse health outcomes and to identify additional data needed to conduct such analyses. Currently available community drinking water data from the Safe Drinking Water Information System (SDWIS) are limited in their application to environmental public health tracking and research. Community water systems (CWS) regularly collect drinking water samples to test water quality and monitor compliance with regulations, but sample collection is often too infrequent to capture seasonal variations in contaminant levels. This is a critical data gap when considering the associations between drinking water contaminants and adverse birth outcomes with specific windows of susceptibility during fetal development that may be on the order of weeks or months. Most states do not have or do not make available the boundaries for their CWS, which prevents linking drinking water data to the population served. Further, additional information is needed about contaminant concentrations at the tap, use of home treatment systems for drinking water, and levels of consumption of CWS drinking water.

The University of Illinois, Chicago (UIC) has improved our understanding and use of available drinking water data by evaluating the features of CWS atrazine and nitrate data from eight states and the effects of the data limitations on the utility of these data for tracking and research (Jones et al., 2013). The team found that monitoring complied with regulatory requirements, but contaminants levels below the limit of detection produced a high percentage of left-censored data, which combined with infrequent sampling would make linkage with health outcome data difficult. However, they did note that contaminants found at higher concentrations were monitored more frequently, thus those contaminants may be better candidates for linkage with health outcome data. UIC explored using a multiple imputation method to address the data gaps caused by censoring and infrequent sampling (Jones et al. submitted to journal). After introducing four different patterns of missing data, they showed that the imputation model could predict the missing data but only when it included synthetic health outcome data with a known association between the contaminant and health outcome. Given the lack of information on etiology and level of association between many water contaminants and health outcomes from epidemiologic and toxicological studies, these methods use may be limited.

UIC demonstrated how related but non-environmental or exposure monitoring data can be used to approximate exposure to environmental hazards. They conducted an ecologic analysis of the association between county level measures of crop-specific agricultural production and adverse birth outcomes in Missouri (Almberg et al. 2014, in press). They substituted crop-specific density for exposure to specific pesticides and found an association between cotton and rice densities and adverse birth outcomes. Despite limitations of the ecologic analysis, including limited data on confounding factors, this study had the statistical power and variability in both exposure and outcome to detect small risks. This analysis suggests that surrogate measures of pesticide exposure can be useful in generating hypotheses and directing further investigations and interventions. They are continuing to explore the associations between adverse outcomes and atrazine exposures by using more extensive data that has been collected for the EPA’s Atrazine Monitoring Program and by using individual birth outcome data from two states.

The University of Utah (Utah) also has contributed to our understanding and use of available drinking water data. They reviewed methods for estimating exposure to contaminants in community drinking water. They found that a dasymetrically apportioned population method, which used ancillary data to differentiate between populated and unpopulated areas within a spatial unit, that produced spatial distributions of the population that are more accurate than areal apportionment methods based only on spatial relationships such as centroid assignment. Utah evaluated methods to link data on arsenic and disinfection byproducts in drinking water with adverse birth outcomes by conducting four parallel analyses: county level ecologic, CWS level ecologic, semi-ecologic using county exposure and individual health data, and individual level using individual data for exposure and health. Results varied inconsistently for all exposures and outcomes across all study designs. CWS level ecologic analysis compared slightly better with individual level results, however, the results of the semi-ecologic and ecologic analyses corresponded for some exposures and outcomes. Given the limitations of using drinking water data, linking data at the individual level may not be possible although a semi-ecologic or ecologic study design using CWS-assigned exposure as opposed to county-assigned exposure may be sufficient. To do that, more effort is needed to link individuals to their primary CWS and then to maintain information needed regarding CWS characteristics and boundaries.

5. Discussion

The Tracking Program's engagement of academia has advanced our understanding of existing health, exposure, hazard, and population data; illustrated where and how data improvements could be made; increased the use of available methods; and contributed to our understanding of what we should track. Our academic partners illustrated that, in some cases, data gaps can be addressed without collecting additional data. They showed how to use related data to approximate missing data and demonstrated or enhanced the methods employed to do so. By using a machine-learning approach and data from multiple sources, new data for important confounders and air pollution have been generated (Beckerman et al., 2013; Ortega et al., 2014). Data on crop-specific density was used to track the association between agricultural production and adverse birth outcomes (Almberg et al., 2014, in press). Our academic partners also showed that compensating for some gaps is difficult without additional data collection. Preliminary reports from UCB and PITT indicate that while an important survey for public health practice, using NHANES data for tracking is limited because of the sampling framework and lack of spatial coverage. To improve the utility of CWS data, service area boundaries are needed. However, the Topic 4 projects did show that it is possible to link CWS data and health data while addressing some of the limitations in the CWS data (Jones et al., submitted to journal). To expand the use of available methods, academic partners provided training, programing code, enhanced software, and technical assistance. They illuminated sources of bias and the effect of method decisions in ecological and semi-ecological analysis using CWS data and provided suggestions for addressing them. They also increased our understanding of what to track by identifying additional exposures and cardiovascular endpoints for tracking the effect of air pollution on health(Brink et al., 2013; Talbott et al., 2013; Talbott et al., 2014).

While these projects have been successful in advancing the science of tracking, they were hindered by data access and availability. Data access procedures vary from state to state and institution to institution. Gaining access to enough data for a regional or national analysis is challenging and resource intensive. Academic partners often are forced to make compromises in their analysis because the necessary data are either unavailable or inaccessible. Protecting confidentiality and ensuring proper use of data are important responsibilities of data stewards; however, improvements could be made in the procedures for requesting and granting access to data.

The topics of these contracts were designed to address challenges faced by federal, state, and local Tracking Program partners. Many of these projects were collaborations between the academic partners and state and local health departments. However, more effort is needed within the Tracking Program to better connect the research and academic expertise with the questions and challenges of the front lines of public health practice. Academic partners want to know how best to contribute. State and local partners want to be at the table when protocols are developed and data are analyzed to ensure their needs are met. Collaboration between the Tracking Program and academic partners to disseminate the results of academic research and translate them for application to the front lines could help create that critical linkage and meet state and local needs. The Tracking Program routinely hosted training sessions at meetings and workshops as an opportunity to disseminate methods and data developed or enhanced by our academic partners. Several publications have been added to the literature beyond the ones in this special issue. A Webinar series featuring each academic partner was conducted over the summer of 2013. Results are more easily translated when appropriate connections are made between academics and practitioners from the beginning and fostered throughout collaboration. Additional ways to maintain those connections should be explored.

6. Conclusion

The partnership between the Tracking Program and academia has established crucial connections and started a dialog between academics and public health practitioners at the federal, state, and local levels. We have collaborated on tracking priorities and shared data, tools, and expertise in both directions to address the challenges faced by the Tracking Program. An added benefit was the training of students and new professionals in the concepts of environmental public health tracking. The impact of the work completed under the three year contracts discussed in this paper will be better understood as the findings are put into action. While challenges remain in the science and practice of tracking, we can progress by nurturing the working relationships that have been established, developing standards to organize data for interoper-ability, expanding methods for data integration and analysis, developing workforce expertise, and working collectively toward the goal of data-driven public health actions and policies that address exposures to environmental hazards. The scale and scope of environmental public health tracking is best served by engaging technical experts and public health professionals from many different sectors. As evidenced by the successful collaborations and significant contributions achieved as a result of the recent engagement of academia, these partners have a critical role in advancing the science and practice of environmental public health tracking and should be included as we move forward in this work.

References

Almberg KS, Turyk M, Jones RM, Anderson R, Graber JM, Banda E. A study of adverse birth outcomes and agricultural land use practices in missouri. Environ. Res. 2014 http://dx.doi.org/10.1016/2014.06.016. in press.

Babin SM, Burkom HS, Holtry RS, Tabernero NR, Stokes LD, Davies-Cole JO, et al. Pediatric patient asthma-related emergency department visits and admissions in washington, dc, from 2001-2004, and associations with air quality, socio-economic status and age group. Environ. Health: A Global Access Sci. Source. 2007; 6:9.

Beale L, Abellan JJ, Hodgson S, Jarup L. Methodologic issues and approaches to spatial epidemiology. Environ. Health Perspect. 2008; 116:1105–1110. [PubMed: 18709139]

Beale L, Hodgson S, Abellan JJ, Lefevre S, Jarup L. Evaluation of spatial relationships between health and the environment: the rapid inquiry facility. Environ. Health Perspect. 2010; 118:1306–1312. [PubMed: 20457552]

Beckerman BS, Jerrett M, Serre M, Martin RV, Lee SJ, van Donkelaar A, et al. A hybrid approach to estimating national scale spatiotemporal variability of pm2.5 in the contiguous United States. Environ. Sci. Technol. 2013; 47:7233–7241. [PubMed: 23701364]

Bekkedal MY, Malecki KM, Werner MA, Anderson HA. Using a partnership barometer to evaluate environmental public health tracking activities. J. Public Health Manag. Pract.: JPHMP. 2008; 14:592–595. [PubMed: 18849780]

Brink LL, Talbott EO, Sharma RK, Marsh GM, Wu WC, Rager JR, et al. Do us ambient air lead levels have a significant impact on childhood blood lead levels: results of a national study. J. Environ. Public Health. 2013; 8

Buehler JW, Centers for Disease C, Prevention. CDC's vision for public health surveillance in the 21st century. Morbidity and Mortality Weekly Report: Surveillance Summaries. 2012; 61(Suppl):1–2.

Charleston AE, Wall P, Kassinger C, Edwards PO. Implementing the environmental public health tracking network: accomplishments, challenges, and directions. J. Public Health Manag. Pract.: JPHMP. 2008; 14:507–514. [PubMed: 18849770]

Elliott P, Wartenberg D. Spatial epidemiology: current approaches and future challenges. Environ. Health Perspect. 2004; 112:998–1006. [PubMed: 15198920]

Fortunato L, Abellan JJ, Beale L, LeFevre S, Richardson S. Spatio-temporal patterns of bladder cancer incidence in utah (1973–2004) and their association with the presence of toxic release inventory sites. Int. J. Health Geogr. 2011; 10:16. [PubMed: 21356086]

Frieden TR. Government's role in protecting health and safety. N. Engl. J. Med. 2013; 368:1857–1859. [PubMed: 23593978]

Haley VB, Talbot TO, Felton HD. Surveillance of the short-term impact of fine particle air pollution on cardiovascular disease hospitalizations in new york state. Environ. Health: A Global Access Sci. Source. 2009; 8:42.

Harris G, Thompson WD, Wartenberg D, Fitzgerald EF. The association of $PM_{2.5}$ with full term low birth weight at different spatial scales. Environ. Res. 2014 http://dx.doi.org/10.1016/2014.05.034. in press.

Jarup L. Health and environment information systems for exposure and disease mapping, and risk assessment. Environ. Health Perspect. 2004; 112:995–997. [PubMed: 15198919]

Jerrett M, Arain A, Kanaroglou P, Beckerman B, Potoglou D, Sahsuvaroglu T, et al. A review and evaluation of intraurban air pollution exposure models. J. Expo. Anal. Environ. Epidemiol. 2005; 15:185–204. [PubMed: 15292906]

Jones RM, Graber JM, Anderson R, Rockne K, Turyk M, Stayner LT. Community drinking water quality monitoring data: utility for public health research and practice. J. Public Health Manag. Pract.: JPHMP. 2013

Jones RM, Stayner LT, Demirtas H. Multiple imputation for assessment of exposures to drinking water contaminants: Evaluation with the atrazine monitoring program. Environ. Res. 2014 (submitted to journal).

Kyle AD, Balmes JR, Buffler PA, Lee PR. Integrating research, surveillance, and practice in environmental public health tracking. Environ. Health Perspect. 2006; 114:980–984. [PubMed: 16835047]

Li J, Dawson B. From patchwork to national network: working collaboratively to create a national environmental public health tracking network. J. Public Health Manag. Pract.: JPHMP. 2008; 14:596–599. [PubMed: 18849781]

Lin S, Luo M, Walker RJ, Liu X, Hwang SA, Chinery R. Extreme high temperatures and hospital admissions for respiratory and cardiovascular diseases. Epidemiology. 2009; 20:738–746. [PubMed: 19593155]

Litt J, Tran N, Malecki KC, Neff R, Resnick B, Burke T. Identifying priority health conditions, environmental data, and infrastructure needs: a synopsis of the pew environmental health tracking project. Environ. Health Perspect. 2004; 112:1414–1418. [PubMed: 15471735]

Love D, Rudolph B, Shah GH. Lessons learned in using hospital discharge data for state and national public health surveillance: Implications for centers for disease control and prevention tracking program. J. Public Health Manag. Pract.: JPHMP. 2008; 14:533–542. [PubMed: 18849773]

Malecki KC, Resnick B, Burke TA. Effective environmental public health surveillance programs: a framework for identifying and evaluating data resources and indicators. J. Public Health Manag. Pract.: JPHMP. 2008; 14:543–551. [PubMed: 18849774]

Mather FJ, White LE, Langlois EC, Shorter CF, Swalm CM, Shaffer JG, et al. Statistical methods for linking health, exposure, and hazards. Environ. Health Perspect. 2004; 112:1440–1445. [PubMed: 15471740]

Matte TD, Cohen A, Dimmick F, Samet J, Sarnat J, Yip F, Jones N. Summary of the workshop on methodologies for environmental public health tracking of air pollution effects. Air Qual Atmos Health. 2009; 2(4):177–184. [PubMed: 20098504]

McGeehin MA, Qualters JR, Niskar AS. National environmental public health tracking program: bridging the information gap. Environ. Health Perspect. 2004; 112:1409–1413. [PubMed: 15471734]

McGeehin MA. National environmental public health tracking program: providing data for sound public health decisions. J. Public Health Manag. Pract.: JPHMP. 2008; 14:505–506. [PubMed: 18849769]

Ortega A, Jerrett M, Davies M, Mann JK, Jesdale B, Jarjour S, et al. Developing a predictive model for smoking prevalence in the united states for use in environmental public health tracking. Environ. Res. 2014 (submitted to journal).

Ozkaynak H, Glenn B, Qualters JR, Strosnider H, McGeehin MA, Zenick H. Summary and findings of the EPA and CDC symposium on air pollution exposure and health. J Expo Sci Environ Epidemiol. 2009; 19(1):19–29. [PubMed: 18560447]

Patridge J, Namulanda G. Describing environmental public health data: Implementing a descriptive metadata standard on the environmental public health tracking network. J. Public Health Manag. Pract.: JPHMP. 2008; 14:515–525. [PubMed: 18849771]

Paulu C, Smith AE. Tracking associations between ambient ozone and asthma-related emergency department visits using case-crossover analysis. J. Public Health Manag. Practice: JPHMP. 2008; 14:581–591.

Pew Commission. America's environmental health gap: Why the country needs a nationwide health tracking network. Johns Hopkins School of Hygiene and Public Health, Department of Health Policy and Management; 2000. http://healthyamericans.org/reports/files/healthgap.pdf

Rabito FA, Iqbal S, Shorter CF, Osman P, Philips PE, Langlois E, et al. The association between demolition activity and children's blood lead levels. Environ. Res. 2007; 103:345–351. [PubMed: 17140560]

Ritz B, Tager I, Balmes J. Can lessons from public health disease surveillance be applied to environmental public health tracking? Environ. Health Perspect. 2004; 113:243–249. [PubMed: 15743709]

Shin HH, Cakmak S, Brion O, Villeneuve P, Turner MC, Goldberg MS. Indirect adjustment for multiple missing variables applicable to environmental epidemiology. Environ. Res. 2014 http://dx.doi.org/10.1016/2014.05.016. in press.

Talbot TO, Haley VB, Dimmick WF, Paulu C, Talbott EO, Rager J. Developing consistent data and methods to measure the public health impacts of ambient air quality for environmental public health tracking: progress to date and future directions. Air Qual. Atmos. Health. 2009; 2:199–206. [PubMed: 20098503]

Talbott EO, Rager JR, Brink LL, Benson SM, Bilonick RA, Wu WC, et al. Trends in acute myocardial infarction hospitalization rates for us states in the cdc tracking network. PloS one. 2013; 8:e64457. [PubMed: 23717617]

Talbott EO, Rager JR, Benson SM, Brink LL, Bilonick RA, Holguin F. A case crossover analysis of the impact of pm2.5 on cardiovascular disease hospitalizations for selected cdc tracking states. Environ. Res. 2014 http://dx.doi.org/10.1016/2014.06.018. in press.

Thacker SB, Berkelman RL. Public health surveillance in the united states. Epidemiol. Rev. 1988; 10:164–190. [PubMed: 3066626]

Thacker SB, Stroup DF, Parrish RG, Anderson HA. Surveillance in environmental public health: issues, systems, and sources. Am. J. Public Health. 1996; 86:633–638. [PubMed: 8629712]

Vaidyanathan A, Dimmick WF, Kegler SR, Qualters JR. Statistical air quality predictions for public health surveillance: evaluation and generation of county level metrics of pm(2.5) for the environmental public health tracking network. Int. J. Health Geogr. 2013; 12:12. [PubMed: 23497176]

Wartenberg D, Thompson WD, Fitzgerald EF, Gross HJ, Condon SK, Kim N, et al. Developing integrated multistate environmental public health surveillance. J. Public Health Manag. Pract.: JPHMP. 2008; 14:552–561. [PubMed: 18849775]

Wilhelm M, Meng YY, Rull RP, English P, Balmes J, Ritz B. Environmental public health tracking of childhood asthma using california health interview survey, traffic, and outdoor air pollution data. Environ. Health Perspect. 2008; 116:1254–1260. [PubMed: 18795172]

Young LJ, Gotway CA, Yang J, Kearney G, DuClos C. Assessing the association between environmental impacts and health outcomes: a case study from florida. Stat. Med. 2008; 27:3998–4015. [PubMed: 18320551]

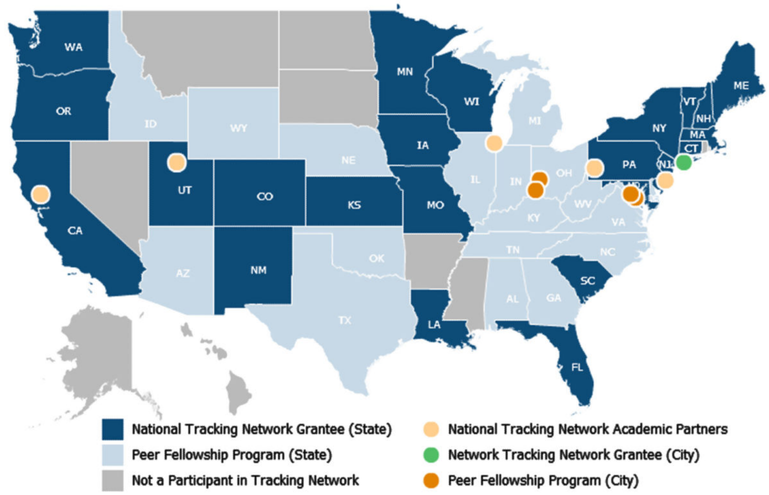

Fig. 1.

Tracking grantees and partners (intended for color reproduction on the Web) http://www.cdc.gov/nceh/tracking/flashmap.html.

Table 1

Topics and awarded projects.

Topic	Goal	Awardee	Project
Development of environmental epidemiologic and statistical methods for use on the tracking network	To define statistical principles and methods that support analytic tools and methods to allow environmental public health practitioners the ability to evaluate spatial and temporal relationships between selected environmental factors and health effects.	University of California Berkeley, PI Michael Jerrett, PhD	A multi-level geographic model for environmental public health tracking
Development of environmental exposure sssessment methods for use on the tracking network	To advance the utilization of these (air and water quality) data and other data to characterize potential exposures of populations to environmental contaminants	University of Pittsburgh, PI Evelyn Talbot, DrPH	Ecological and case control study of ambient air levels and childhood blood lead levels
Linkage study of air quality PM and cardiovascular effects data from the tracking network	To utilize these (PM 2.5 and hospitalizations) data to increase our understanding of the association of PM2.5 with cardiovascular effects as well as identify additional data needed to conduct these analyses	University of California Berkeley, PI John Balmes, MD	PM2.5-cardiovascular disease associations: use of modeled hierarchical bayesian vs ambient monitoring exposure data: use of census-based geographic and lifestyle variables; exploration of biomarkers of exposure and effect
		University of Pittsburgh, PI Evelyn Talbot, DrPH	Linkage study of air quality PM2.5 and cardiovascular effects data from the tracking network
		UMDNJ, PI Dan Wartenberg, PhD	Linkage study of air quality PM2.5 and cardiovascular effects data from the tracking network
Linkage study of exposure data from safe drinking water information system (SDWIS) and health outcome data from the tracking network	To utilize these (drinking water) data to increase our understanding of the association of between specific drinking water contaminants and adverse health outcomes as well as identify additional data needed to conduct these analyses.	University of Illinois-Chicago, PI Leslie Stayner, PhD	A linkage study of health outcome data in children and agrichemical water contamination data in the Midwest
		University of Utah, PI-Jim VanDerslice, PhD	Advancing the science of linkage studies between drinking water contaminants and adverse birth outcomes