Commentary

Prospects and Pitfalls of Occupational Hazard Mapping: ‘Between These Lines There Be Dragons’

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Hazard data mapping is a promising new technique that can enhance the process of occupational exposure assessment and risk communication. Hazard maps have the potential to improve worker health by providing key input for the design of hazard intervention and control strategies. Hazard maps are developed with aid from direct-reading instruments, which can collect highly spatially and temporally resolved data in a relatively short period of time. However, quantifying spatial–temporal variability in the occupational environment is not a straightforward process, and our lack of understanding of how to ascertain and model spatial and temporal variability is a limiting factor in the use and interpretation of workplace hazard maps. We provide an example of how sources of and exposures to workplace hazards may be mischaracterized in a hazard map due to a lack of completeness and representativeness of collected measurement data. Based on this example, we believe that a major priority for research in this emerging area should focus on the development of a statistical framework to quantify uncertainty in spatially and temporally varying data. In conjunction with this need is one for the development of guidelines and procedures for the proper sampling, generation, and evaluation of workplace hazard maps.

Keywords: aerosols; Bayesian statistics; direct-reading instruments; exposure assessment; exposure assessment methodology; exposure variability; radiation; risk assessment

INTRODUCTION

Early navigational maps often contained depictions of sea monsters and mythical beasts lying in wait at the boundaries of the known world. Such warnings served as a reminder for the perils of open sea travel and for the uncertainty that accompanied anyone brave (or foolish) enough to travel beyond the map’s edge. The Lenox Globe (circa 1510), for example, gives reference to dragons off the Eastern coast of Asia (‘hic sunt dracones’ or ‘here be dragons’ is inscribed therein). The phrase ‘Beyond this place there be dragons’ has since become widespread in various forms of fictional and historical media, while the essential warning remains the same. Our play on this phrase, and the subject of this commentary, is to suggest that uncertainty (and perhaps danger) also exists ‘within the map’, as has become evident with the emergence of maps depicting workplace hazards. We define ‘hazard mapping’ (loosely at present since the technique is still evolving) as: the depiction of relative levels of a quantifiable hazard as it varies across a geographical space. In the realm of occupational hygiene, this means projecting the intensity or concentration of a physical or chemical agent onto a two-dimensional floor plan or layout of a workplace. Below, we discuss advantages and limitations of workplace hazard

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mapping, followed by suggestions for research and future work. However, to understand the advent of occupational hazard mapping, one must first appreciate the tools that make these maps possible: direct-reading instruments.

Over the past few decades, direct-reading instruments, which we define as those providing highly time-resolved and near-instantaneous measurement data, have emerged as a new tool for assessing workplace hazards. Such instruments are available for numerous physical (e.g. noise, vibration, radiation) and chemical agents (e.g. aerosol, gas, vapor) (Todd and Leith, 1990; Fischer et al., 2001; Peters et al., 2006; Benton-Vitz and Volckens 2008; Thai et al. 2008; Fernandez et al., 2009; Hammond et al. 2009; Prlic et al., 2009). They are typically portable, allowing the user to make highly spatially resolved measurements. Thus, they are often employed as survey tools for locating the ‘source and extent’ of a hazard or as personal monitors for estimating an individual’s exposure during a task or workshift. Direct-reading instruments can also be useful when assessing hazards for which no standard method exists as is often the case with emerging hazards such as airborne nanoparticles. Because of their portability and rapid response rate, direct-reading instruments have enabled the collection of unprecedented levels of spatially and temporally resolved data, which, in turn, has driven new innovations in the field of exposure assessment and risk communication.

One example is video exposure monitoring, where data from a direct-reading instrument are coupled to a video recording. With video exposure monitoring, video footage and time-resolved exposure data are integrated by receiving software that displays both signals simultaneously on a computer monitor so that the intensity of a given hazard may be contrasted against a particular work practice. This integration allows the hygienist to visualize the transient nature of exposure as the worker performs their job duties. In a recent review, McGlothlin (2005) stated that ‘pinpointing exposure sources (with video exposure monitoring) led to cost-effective controls and the development of an effective feedback mechanism’ for communication between industrial hygienists, workers, and management. In effect, video exposure monitoring provides workers and management with a means to see when and how job practices translate into exposure. This technique has been especially successful in correlating musculoskeletal disorders with repetitive work tasks and in investigating personal and environmental factors associated with aerosol generation and control (Rosen et al., 2005).

A second innovation, and the subject of this commentary, involves the relatively new practice of using direct-reading instruments to ‘map’ hazards throughout a workplace. Whereas video exposure monitoring typically characterizes temporal patterns of exposure in a fixed space, hazard maps characterize spatial patterns of exposure for a given period of time. Hazard maps represent a natural evolution in the process of exposure assessment, given the emergence of data collection methods with high spatial and temporal resolution. For example, Peters et al. (2006) mapped aerosol mass and number concentrations in an automotive machining facility; an example map from one day of their sampling campaign is reproduced from their data and presented in Fig. 1. The striking feature of this map is how quickly one can interpret the extent of the aerosol hazard as it varies throughout the factory. Not only are the source locations evident, but one can also appreciate the extent to which the hazard has dispersed throughout the workplace atmosphere.

The use of occupational hazard maps is becoming more common (O’Brien, 2003; Heitbrink et al., 2007; Liu and Hammond, 2010; Park et al., 2010). The GridMap method, a relatively early example, was developed for mapping trace gas concentrations on a coarse grid with the use of a photoionization detector (Rosén et al., 1990; Andersson et al., 1993). Hazard maps have also been used to guide interventions that benefit worker health. O’Brien (2003) mapped concentrations of metal removal fluid mists within a metal machining plant where 30 employees had been diagnosed with hypersensitivity pneumonitis. After implementing controls based on the original survey, aerosol concentrations were again mapped and showed significant declines. Only one new case of occupational hypersensitivity pneumonitis was reported in the subsequent 2 years.

USING MAPS TO COMMUNICATE RISK

The use of maps to describe health hazards is not new, as Dr John Snow so eloquently demonstrated during a cholera outbreak in London in the summer of 1854 (Snow, 1855). Using a map of London, Snow tracked the locations of cholera deaths in a severely afflicted region of the city (Fig. 2). Snow also marked the locations of public water pumps, following an emerging theory that drinking water may be related to the spread of the disease (Brody et al., 2000). With this seminal data map, Dr Snow demonstrated both the ‘source’ (Broad St. water pump) and ‘route’ (contaminated drinking water) of cholera exposure in dramatic fashion. Today, similar, albeit
more advanced techniques are commonplace in the field of environmental epidemiology, where geography and spatial statistics are used in concert to associate environmental contaminants with the incidence and prevalence of human disease (Nuckols et al., 2004).

With the advent of portable direct-reading instruments, it is not surprising that the ‘mapping’ of workplace hazards has begun to emerge in the field of occupational hygiene. Hazard maps can benefit the practicing hygienist in several ways. For example, the map developed by Peters et al. (Fig. 1) identifies not only the source of respirable particles but also the extent of contaminant dispersion throughout the factory. Hazard maps can also aid risk communication; a well-designed map provides the observer with a wealth of information in a readily digestible and easily communicable format. Even a casual observer can point to the bottom of Fig. 1 and identify areas of high risk. Thus, hazard maps can serve as a medium to promote effective communication between the hygienist, the worker, and management. However, as with any emerging technology, there are potential limitations and knowledge gaps associated with its use. Below, we highlight potential pitfalls of workplace hazard mapping, followed by recommendations for future research.

**PITFALLS AND LIMITATIONS OF WORKPLACE HAZARD MAPS**

A map is only as reliable as the measurements used to make it, and direct-reading instruments can suffer from various forms of measurement error (e.g. poor accuracy or precision, lack of sensitivity, and bias from interferences). Such errors affect all measurement methods (including more traditional, time-integrated techniques) and tend to be instrument- and/or technique-specific (American Conference of Governmental Industrial Hygienists, 2001). We do not address instrument error here, instead focusing on two additional forms of measurement error particularly relevant to data mapping: completeness and representativeness of measurements. The first error, completeness, stems from the fact that one cannot measure a hazard at all locations and times simultaneously, which implies that some degree of interpolation is needed to generate a hazard map. The second and related error, representativeness, stems from the fact that interpolation of data collected through space and time may lead to errors in estimates and misrepresentation of the sample variance. In other words, because short-term measurements may only reflect temporary conditions, such measurements may not
capture exposure variability over longer time periods, potentially leading to error in the subsequent map. Such errors may then lead to incorrect conclusions, unsatisfactory performance of an intervention, or unnecessary cost for control and surveillance. Depending on the sampling scheme, these errors can be random or systematic in nature. If errors are random, then measurement uncertainty (about an estimated mean) can be reduced with replicate measurements. However, if data are correlated, additional measurements provide less information due to a lack of data independence. Emissions from many indoor sources are not constant but are associated with occupant activities (Luoma and Batterman, 2000). Thus, investigators have found that indoor concentrations are generally highly variable and autocorrelated in both space and time, leading to an underestimation of variance with consecutive measurements (Francis et al., 1989).

We provide below an example of how sources and exposures may be mischaracterized in a hazard map due to a lack of completeness and representativeness of the collected measurement data. Consider the layout of a hypothetical factory where emissions from three contaminant sources are simulated in time (Fig. 3). The contaminants emanating from these sources (and their relative magnitudes) are arbitrary, but for this discussion, they may be envisioned as radiative emissions that travel quickly through space. To simulate contaminant release...
and dispersion in this hypothetical environment, we make the following simplifying assumptions.

**Known emission rate**

Each source is assumed to represent a different process with emissions that vary in time (500 time steps for this simulation). These time steps are also arbitrary but may be thought of as minutes for practicality, corresponding to roughly an 8-h workshift that runs from 9 a.m. to 5 p.m. Source 1 is ‘active’ and nearly constant throughout the day. Source 2 represents a batch-type process that turns on and off multiple times during a workshift. Source 3 represents a ‘ramping’ process with a gradual increase in emissions followed by a gradual decrease over time.

**Immediate and uniform dispersion**

Contaminant levels at each location in the facility are at instantaneous steady state with the emissions from the three sources. This assumption is more valid for agents such as noise or ionizing radiation but less so for other physical or chemical agents that are transported relatively slowly by phenomena such as diffusion and convection.

**Square law**

Contaminant concentration (or intensity) decays according to the inverse square of the distance from the source. This assumption generally applies to radiative emissions, which we chose for the sake of simplicity. Therefore, we will refer to contaminant levels in terms of ‘intensity’; however, the term ‘concentration’ could also be applied. Further, we assume that the contaminant dispersion will be adequately represented in two dimensions (i.e. we assume that vertical dispersion is negligible compared to radial dispersion in the plane extending horizontal to the source). This assumption is more reasonable for radiative emissions but less likely valid for aerosols or for gaseous emissions where contaminant density is substantially different from that of air.

**No convection, reflection, or reaction**

Effects from ventilation sources, resuspension, surface-reflection, or other concentration modifiers are not included.

**No instrument or user error**

Measurements made by an individual using a direct-reading instrument within the facility are 100% accurate.

Although these assumptions dramatically reduce the complexities of actual contaminant release, dispersion, and decay, they serve to demonstrate potential pitfalls of data mapping even for a simplified industrial environment.

Using these assumptions, we calculated contaminant intensity levels at every location in the room (10,000 coordinates in Cartesian space) across 500 time steps. This simulated dataset, for the purpose
of this discussion, contains the ‘true’ values of contaminant intensity through space and time. We have provided maps of the instantaneous contaminant intensity (log scaled) within the facility at three different times (9 a.m., 1 p.m., and 4 p.m.), shown in Fig. 4 (note that the corresponding time profiles for source emissions are provided in Fig. 3). These maps represent a snapshot of a hazard surface that is constantly varying throughout the course of the day. We have plotted these data two different ways for illustrative purposes: the top panel of Fig. 4 shows contaminant intensity on the z-axis and the bottom panel shows the same data as colored isopleths in two-dimensional form.

At 9 a.m., only Source 1 is operating, and thus only one contaminant peak is present on the map. At 1 p.m., two sources are operating and two peaks are evident from Sources 1 and 3. At 4 p.m., Sources 1 and 2 are on and give large peaks on the map, but only a small peak is visible from Source 3. A time-lapse video showing the full evolution of the two-dimensional intensity profile is provided as Supplementary data, available at Annals of Occupational Hygiene online. Examination of Fig. 4 highlights a key limitation of most data maps: they lack an inherent ability to convey ‘temporal’ trends in spatially resolved data.

Because we are also interested in long-term risks from cumulative exposure, we may describe contaminant concentrations across the facility in the form of an 8-h time-weighted average (TWA), as shown in Fig. 5. This TWA map does not convey temporal variation in contaminant intensity, but it does represent average, daily levels encountered across the factory. Examination of the Figure clearly shows the location and relative magnitude of each source. With knowledge of worker proximity to these sources, one could model cumulative exposure or develop strategies for exposure intervention such as process substitution, elimination, or engineering controls.

Let us now conduct a theoretical ‘walkthrough’ of this facility to make measurements for the development of a hazard map. We must acknowledge, however, that constraints on instrumentation and personnel limit the sampling process; one cannot measure concentrations at every point in space and at all times. In practice, hazard maps are typically created using measurements from one or more direct-reading instruments during a traverse across a facility over a finite period of time (O’Brien, 2003; Peters et al., 2006). The traverse may be repeated to evaluate measurement reproducibility, as was demonstrated by Peters et al. (2006). During the traverse, location and hazard intensity data are recorded simultaneously with aid from automated positioning systems (i.e. GPS) or other location tracking methods. From these data, a hazard map is developed using graphical software, often in conjunction with some level of interpolation to develop a smoothed estimate of the concentration surface.

To mimic this practice, we define a theoretical measurement campaign carried out by an individual.

![Fig. 4. Simulated hazard maps at the facility at three selected times. The top panels depict a three-dimensional representation of hazard intensity through space; the bottom panels present the same data in two-dimensional form where variation in hazard intensity is represented by color.](image-url)
who moves through the facility taking periodic measurements at pre-defined locations (see Fig. 3 for sample locations). The individual begins in one corner of the facility and measures the contaminant intensity at that location during the time Step 1. This individual then moves a distance of 10 grid points (10 m) and records a measurement at time Step 2. Sampling in this fashion across the entire facility would require 120 time steps (~2 h), generating data at 10-m intervals in space (including along the walls). This methodology is similar to those currently reported in the literature (O’Brien, 2003; Peters et al., 2006; Liu and Hammond, 2010). Since we know the true intensity at all points and times, and we assume that all measurements are perfectly accurate, we can extract the 121 ‘measured’ data points from our simulated dataset and use these data to generate a ‘sampled’ intensity map, as shown in Fig. 6. The data in Fig. 6 do not contain any interpolated values. Instead, we have simply connected adjacent points to define a measured hazard surface (and the same is true for Figs 4 and 5).

Comparison of Figs 5 and 6 indicates serious discrepancies between the sampled map (Fig. 6a) and the TWA map (Fig. 5). The sampled map tends to underestimate contaminant intensity at most locations throughout the facility (as compared to the TWA). The percent error between the sampled hazard map and the true TWA map is shown graphically in Fig. 6b as isopleths of percent difference. Concentrations were over and underestimated by up to 75% in different regions of the facility. Taken over the entire surface, the average percent error in absolute terms is ~45%. This comparison illustrates the fact that, due to practical limitations on the completeness of sampled data, hazard maps can be both unrepresentative and inaccurate. The sampled map from this example...
is not useless—it does provide a reasonable indication of the locations of Sources 1 and 2 along with a qualitative indication of source strength. However, the map is not accurate from a quantitative standpoint, which could affect exposure assessment, risk analysis, and decision making, especially if compliance with a prescribed occupational exposure limit is of interest. The extent of these errors raises several questions. What level of data completeness will ensure adequate representativeness? And how does one evaluate the completeness and representativeness of their data without prior knowledge of the true hazard map? Such questions have yet to be examined in great detail in the occupational hygiene literature.

The sampling strategy used to generate the data shown in Fig. 6a, although plausible, was somewhat arbitrary. Different sampling schemes may be devised or employed at different times of day that produce more (or less) representative data maps. For example, if the sampling campaign began at 11 a.m. or 2 p.m., then the average absolute error between the sampled hazard map and the true TWA map would be 55 and 58%, respectively. If the user were to make two passes through the facility (taking 4 h to complete the measurements), making one repeated measure at each location, then the average percent error between the true and sampled map reduces to ~26%.

In addition to the timing of the measurements, the resolution of the sampling grid can also affect accuracy. The maps developed by Peters et al. (Fig. 1) were conducted at two levels of grid resolution (59 and 102 grid locations within the same measurement space). They found that, for maps of aerosol number concentration, fine grids only provided slightly more information than coarse grids. However, regions of high mass concentration that were resolved on the fine grids were missed on the coarse grids. As a result, Peters et al. (2006) noted that coarse-grid mapping techniques may not be sufficient in facilities where source emissions are not steady state.

These examples reiterate the well-known principle that understanding sample variability (i.e. through the collection of repeated measures) is integral to any reliable exposure assessment (e.g. Rappaport, 1991). Historically, variability in exposure data has been described as subject-related (within-person or within-group) and job- or task-related (between groups). In the context of hazard mapping, assuming no instrument or user error during sampling, measurement variability has two important facets: spatial variability and temporal variability.

The issue is determining (preferably a priori or in situ) what degree of completeness in the collected hazard data will ensure adequate representativeness of the subsequent hazard map. In other words, we must ensure confidence in our data by knowing how many points to sample, how far apart (in both space and time) the samples should be taken, and how many repeated measures should be made. Unfortunately, this is not a well-posed problem from the standpoint of experimental design. In geography, measures such as distance and elevation are assumed to be static in time. Contaminant levels, on the other hand, vary considerably through space and time and may or may not be adequately represented with a single measurement at a given location. For hazard mapping in occupational hygiene, both spatial and temporal variability play a contributing role in measurement uncertainty. Complicating the issue is the fact that spatial and temporal variability are not independent; they are coupled and correlated in complex ways. This coupling complicates statistical treatment of sampled data (Symanski and Rappaport, 1994; Host et al., 1995; Kolovos et al., 2010).

HAZARD MAPPING TOOLS

Anyone can attest to the frustration that comes with trying to follow directions from a faulty map. So how does one go about making a good hazard map? And how can we assure ourselves that our map is representative? There are many possible sampling and data interpolation schemes that can be used to generate a hazard map. Yet, despite the challenges associated with collecting and analyzing spatial–temporal data, there are techniques from other scientific fields that we may employ to aid our understanding. For example, methods have been developed for mapping ambient air pollution concentrations based on data from outdoor monitoring networks. These studies have examined the spatiotemporal distribution of ozone (e.g. Liu and Rossini, 1996; Nikiforov et al., 1998; Wong et al., 2004), particulate matter (e.g. Puangthongthub et al., 2007; Pollice and Lasinio, 2010), and trace gases (e.g. Setton et al., 2008; Beelen et al., 2009).

Spatial techniques: kriging

A simple approach to hazard mapping is to ignore the temporal variation and examine only the spatial variation of the data. That is, assume that all measurements are taken at a single time (neglecting the finite time required to collect such data). Otherwise, we may acknowledge that measurements were taken repeatedly at a number monitoring stations (e.g. weather stations) and a map is generated that represents an average over time. With this assumption, one can employ Kriging to interpolate spatial data.
Traditional Kriging is a mapping method that provides an optimal interpolation by minimizing a mean squared error among weighted linear combinations of observed data. Traditional Kriging employs a variogram, a statistical summary that compares measured values in space to the distances that separate them, which is often displayed graphically. The variogram helps to evaluate the correlation between measurements, so that a weighting function may be devised to aid spatial interpolation (i.e. the estimation of data values at unsampled locations). The weighting function places more emphasis on measurements located within an appropriate range of spatial dependence (Beelen et al., 2009). Traditional Kriging brings several advantages to data mapping: (i) it interpolates observations using optimized weights that depend on variograms, (ii) it provides an estimate of the spatial interpolation error, which can be used to evaluate the representativeness of the generated map, and (iii) it ensures that the estimate at any sampled location remains as the observed value (Liu and Rossini, 1996). Traditional Kriging can account for spatial trends that may be considered constant but unknown (i.e. Ordinary Kriging) or an unknown function of location (i.e. Universal Kriging). This is important since spatial gradients can point to possibly unrecognized point sources (Le and Zidek, 2006).

Spatiotemporal techniques: bayesian methods

As demonstrated with Figs 5 and 6, a single short-term measurement at one point may not adequately represent all the conditions at that point throughout the course of time. The extent of ‘temporal variation’ in hazard intensity throughout the facility is shown in Fig. 7. This Figure depicts isopleths of the relative standard deviation (percentage units) of simulated intensity at each point across the entire day. Areas with relatively small changes in intensity are shown in blue; areas where the intensity changes substantially throughout the day are shown in red. Note that the temporal standard deviation near Source 1, with relatively constant emissions, is small, whereas the standard deviations near Sources 2 and 3 are much larger.

Traditional Kriging was not designed to account for temporal variation and, therefore, may not be appropriate for hazard mapping in locations with time-varying emissions (which is likely the case for most industrial settings). Bayesian Kriging methods have been developed to account for the interaction of the spatial and temporal variances (e.g. Le and Zidek, 2006). Spatiotemporal Kriging results in a concentration map and variance map for each time step; the latter contains information on both spatial and temporal uncertainty. By averaging over the maps, it may be possible to obtain a mean concentration map and mean variance map (Fanshawe et al., 2008). The variogram associated with this method relates both spatial and temporal dependence among separate measures. For simplicity, it is often assumed that dependence structures over time and space are separable, and thus the variogram can be represented by separate spatial and temporal correlation functions. However, this assumption is not consistent with contaminants that disperse according to convective-diffusion equations and conservation laws of mass, momentum, and energy. This method also generally assumes that many repeated measures are periodically taken from an array of fixed monitoring sites. This type of array-based monitoring has not been used for workplace hazard mapping and may not be feasible given the associated costs.

Another technique that has potential for application in workplace hazard mapping is Bayesian Maximum Entropy (BME). This technique has been used for mapping air pollutants (Christakos and Serre, 2000a), soil properties (Bogaert and D’Or, 2002; Douaik et al. 2004), disease outbreaks (Law et al., 2006), and exposure-induced health effects (Christakos and Serre, 2000b). The BME method allows one to “integrate rigorously and efficiently various forms of physical knowledge and sources of uncertainty” (Christakos and Serre, 2000a).

BME uses general knowledge (e.g. mean, covariance, multiple-point statistic, scientific laws) in conjunction with case-specific knowledge (i.e. measured intensities). The inclusion of general knowledge, such as convective diffusion equations or
conservation of mass and energy laws, allows for prediction beyond the limits of the measured data (Christakos and Serre, 2000b). Additionally, the BME technique can include “hard” (measured data and ‘soft’ data in the case-specific knowledge (Christakos and Serre, 2000a). An example of soft data may include defining a range of values set by the minimum and maximum values of some number of neighbors or include ‘expert’ knowledge/judgement at missing data points. This is particularly important in cases where there is a limited quantity of measurements available (Christakos and Li, 1998). The inclusion of soft data is not possible with Kriging methods and, through its inclusion, BME results in better estimates and a reduction of the estimation errors (Christakos and Serre, 2000a). In fact, Kriging is a special restrictive case of BME (Christakos, 1990). BME also removes many of the restrictions imposed by Kriging, such as linearity of the estimator, normality of the underlying probability laws, or homogeneity of the spatial distribution (Christakos and Li, 1998). Like spatiotemporal Kriging, the BME technique has yet to be evaluated in the context of workplace hazard mapping.

Measurement techniques in-situ

Each of the aforementioned data analysis techniques was designed to help understand aspects of spatial and temporal variability of ‘previously’ collected data. However, many strategies may also be applied during sample collection that could potentially aid our understanding of spatial–temporal variability (and subsequent data representativeness). Whereas random sampling is always desired, this process can be hindered by the fact that, typically, one monitor must be carried to each measurement point (requiring considerable time resources during a sampling campaign). Thus, one might question whether traditional traverse sampling should be employed (as opposed to random walks or locations) to benefit a larger sample size. The collection of repeated measures (across both space and time) will also likely improve estimates; however, the best way to collect such data is somewhat unclear. For example, should one take multiple measurements at a fixed location for a sustained period of time? Repeated measures using a ‘static monitor’ that is fixed at one location could be used to assess temporal autocorrelation (albeit at only a single location). On the other hand, repeated measures taken at random times (but at the same locations) might provide a more robust estimate of overall data representativeness, especially if the time intervals between measurements were also randomized (with durations of seconds, minutes, days, or longer). Should a static monitor be located near known or suspected sources? Park et al. (2010) suggested using a finer sampling grid near sources and a coarse grid away from sources provided the source locations are known and well delineated. The answers to such questions are, as of yet, unclear and, thus, lay the foundation for an active and needed area for further research.

Of course, this discussion is to say that having more measurements is good but having more instruments to make those measurements may be even better. Indeed, as direct-reading instruments become more cost-efficient, it may be possible to generate maps from a dense network of continuously running monitors. Such systems would eliminate the need for extensive interpolation. At present, however, instrument cost still limits the number of units that can be deployed simultaneously. We note also that instrument-related measurement error, although ignored in our simulations above did not have a significant impact on our results. We examined the influence of a small (10%) random error applied to our measured dataset. Such error could be interpreted as instrument error on the generated maps. However, since the intensities were log-normally distributed, adding 10% noise had virtually no impact on the gross error of the plots. This finding indicates that measurement error may not be as important as error due to an unrepresentative mapping strategy.

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

Several conclusions may be drawn from this discussion. Hazard data mapping is a promising new technique that can enhance the process of exposure assessment and risk communication in occupational hygiene. Occupational hazard maps developed with direct-reading instruments have the potential to improve worker health by providing rapid feedback for intervention and control strategies. This new type of data mapping, which essentially represents a form of discretized repetitive area sampling, will likely not replace the practice of ‘personal’ exposure monitoring in the workplace, the latter being the current state-of-the-art for assessing an individual’s risk from exposure. This is especially true since most occupational exposure limits are regulated and enforced using exposure estimates based on the collection of personal samples. However, data mapping does have the potential to augment the process of risk assessment and risk communication—especially when the goal is to ascertain and minimize workplace hazards, as opposed to evaluating and enforcing.
could be generated from personal sampling data taken with miniature direct-reading instruments. This prospect suggests yet another promising avenue for further research.

Physical and chemical workplace hazards vary through space and time and these variations are not mutually independent. Spatial and temporal variations of contaminant levels in the workplace are related to each other in complex ways as has been reported in both modeling and measurement studies (Symanski and Rappaport, 1994; Host et al., 1995; Kolovos et al., 2010). However, quantifying spatial–temporal variability in the occupational environment is not easily accomplished via measurement and/or modeling.

Our current understanding of how to ascertain and model spatial and temporal variability is a limiting factor in the use and interpretation of workplace hazard maps. Even the simple example presented here demonstrates that a single pass through a facility is unlikely to generate data needed to construct representative hazard maps. As such, the reliability of workplace hazard maps may be questioned, especially if the uncertainties associated with this new form of exposure assessment are not estimated. Although maps currently reported in the literature do provide spatially resolved estimates of hazard intensity, these maps typically do not give any sense of temporal variation (or spatial–temporal uncertainty) of collected data. Peters et al. (2006) did generate multiple hazard maps during two different seasons (summer, winter) to acknowledge the potential for spatial–temporal variability. They found that while respirable mass concentrations were highly variable, ultrafine number concentrations were much more stable throughout a given season. On the other hand, Evans et al. (2008) made repeated measurements of ultrafine particles (for the development of multiple maps) within the same facility and reported highly variable results. These findings lead the authors to question the representativeness of maps developed around unstable contaminant sources.

Hazard maps will be most informative if there is also an estimate of data quality. Assigning confidence to estimates of spatially and temporally varying hazard data is key to understanding the representativeness of any map. Unfortunately, this practice is easier said than done and, admittedly, we are pointing the finger at the problem without providing the means to a solution. However, with additional research, it may be possible to define both data collection and analysis procedures (given limited resources) for the generation of representative data maps in a fashion that also provides a reasonable estimate of data quality.

Based on these conclusions, we believe that new techniques are needed to understand spatial and temporal variability in workplace hazard levels. Many techniques exist to quantify data variability across Cartesian space (e.g. kriging, and BME), and some techniques exist to examine aspects of temporal variability (e.g. autocorrelation). However, few techniques exist to quantify uncertainty in spatial–temporal data simultaneously and none of these techniques have been evaluated in the occupational environment. Therefore, a major priority for research in this emerging area should be centered around the development and evaluation of a statistical framework to quantify uncertainty in spatially and temporally varying measurement data (with particular emphasis on occupational exposure data). In conjunction with this need is one for the development of guidelines to define proper procedures in the sampling, development, and evaluation of workplace hazard maps. In the absence of established guidelines, we recommend that care should be taken during the collection and interpretation of workplace hazard maps. For example, during data collection, one should strive to collect repeated measures (across both space and time) with the finest grid resolution that is cost feasible.

Finally, although we highlight here many potential pitfalls associated with this emerging technique, we also note that ‘risk’ is inherent to the process of exploration. Uncertainty always accompanies the development of new scientific knowledge and should not stifle our efforts to push the boundaries of exposure science outward—how else can we face the ‘dragons’ purported to lie at the edge of the map? In time, we expect that hazard maps will produce substantial benefits for worker health by improving our understanding of dose–response and contaminant control in the workplace.

SUPPLEMENTARY DATA

Supplementary data can be found at http://anhyg.oxfordjournals.org/.

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