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Silica Exposure During Construction Activities: Statistical Modeling of Task-Based Measurements from the Literature

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Many construction activities can put workers at risk of breathing silica containing dusts, and there is an important body of literature documenting exposure levels using a task-based strategy. In this study, statistical modeling was used to analyze a data set containing 1466 task-based, personal respirable crystalline silica (RCS) measurements gathered from 46 sources to estimate exposure levels during construction tasks and the effects of determinants of exposure. Monte–Carlo simulation was used to recreate individual exposures from summary parameters, and the statistical modeling involved multimodel inference with Tobit models containing combinations of the following exposure variables: sampling year, sampling duration, construction sector, project type, workspace, ventilation, and controls. Exposure levels by task were predicted based on the median reported duration by activity, the year 1998, absence of source control methods, and an equal distribution of the other determinants of exposure. The model containing all the variables explained 60% of the variability and was identified as the best approximating model. Of the 27 tasks contained in the data set, abrasive blasting, masonry chipping, scabbling concrete, tuck pointing, and tunnel boring had estimated geometric means above 0.1 mg m^{-3} based on the exposure scenario developed. Water-fed tools and local exhaust ventilation were associated with a reduction of 71 and 69% in exposure levels compared with no controls, respectively. The predictive model developed can be used to estimate RCS concentrations for many construction activities in a wide range of circumstances.

Keywords: construction industry; crystalline silica; monte carlo simulation; multi-model inference; task-based assessment

INTRODUCTION

Occupational exposure to respirable crystalline silica (RCS) containing dust is linked with chronic lung diseases such as silicosis (Leung *et al.*, 2012) and lung cancer (IARC, 2012). The number of workers potentially exposed to RCS is estimated at over 3 million in the European Union, 1.7 million in the USA, and 350 000 in Canada (NIOSH, 2002; Peters *et al.*, 2012). Since the 1990s, the construction sector has been the focus of several studies and initiatives to identify factors associated with RCS exposure (Linch and Cocalis, 1994; Madl *et al.*, 2008), as crystalline silica is a constituent of numerous building materials such as concrete, rock, brick, and sand (Moore, 1999; NIOSH, 2002). Studies by Lumens and Spee (2001), Rappaport *et al*. (2003), and Flanagan *et al*. (2006), among others,

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have highlighted the extent and sources of overexposure for many construction trades and tasks.

The evaluation of exposure to RCS in the construction industry remains challenging due to the important variability in exposure determinants such as tasks, materials, and worksite characteristics, among others. Construction sites involve a variety of constantly changing operations and specialized workers (Chisholm, 1999), and the duration of exposure within a work shift can vary depending on the activities performed (Valiante *et al*., 2004). Many studies (e.g. Chisholm, 1999; Verma *et al*., 2003; Tjoe Nij *et al*., 2004) have sampled a limited number of workers and have cautioned against generalizing their results to the entire industry. Despite the impressive number of measurements contained in their RCS exposure database, Flanagan *et al*. (2006) concluded that additional research is necessary to identify factors contributing to high exposure levels.

In order to identify circumstances associated with hazardous levels of RCS and document the effectiveness of engineering controls, an occupational exposure database of RCS exposure in the construction industry was developed by Beaudry *et al*. (in press). This database was compiled from measurements of RCS and associated determinants reported in the published literature of the last 25 years. It contains measurements of dust and crystalline silica in various fractions such as respirable and inhalable, sampled under different strategies (e.g. task-based and compliance assessment).

Occupational exposure limits to RCS are set as time-weighted averages (over 8 or 10 h) in most jurisdictions (Maciejewska, 2008). However, some studies (e.g. Greenspan *et al*., 1995; Goldberg *et al*., 1997; Susi *et al*., 2000; Kerr *et al*., 2002) have used a task-based exposure assessment strategy for noise and contaminants associated with construction work to improve the characterization of exposure determinants and provide guidance in the selection of appropriate control methods.

The objectives of this study were to estimate RCS exposure levels associated with tasks performed in the construction industry and to quantify the effect of other determinants and exposure control methods, using the database constructed by Beaudry *et al*. (in press).

METHODS

Exposure database

The database was constructed following an extensive literature review of crystalline silica exposure data published between 1987 and 2009. While documenting exposure levels during abrasive blasting was outside the scope of the data compilation project, some results for this task were entered in the database when found alongside RCS exposure data for other construction activities. The database comprises 6118 records of crystalline silica and dust exposure in various forms and fractions, gathered from 115 sources of data. These sources include scientific papers, survey reports (such as NIOSH Health Hazard Evaluations) and existing databases provided by Flanagan *et al*. (2006) and the French Institut de Veille Sanitaire, the latter forming the basis of a job-exposure matrix (InVS, 2011). Each record in the database represent a single measurement, or a set of measurements summarized by statistical parameters—i.e. 2 or more measurements summarized and reported as a geometric mean (GM) and standard deviation (GSD), arithmetic mean or range. The combined sample size of the individual and summarized data represents 11 845 measurements.

Ancillary information in this database includes several parameters describing exposure determinants (e.g. trade, task, construction sector, tool, and material) and sampling methodology (e.g. sampling duration, strategy, location—personal, area or source—and analytical method). The task-based strategy was attributed to exposure results associated with a task or a group of tasks in the source of data, irrespective of sampling duration. The trade, task, tool, and material descriptions were entered in the database as they were reported in the source of data. In addition, the database includes a standardized classification of these variables to facilitate their analysis. For instance, the tasks descriptions of "Removing mortar between bricks," "Grinding mortar between bricks," "Mortar removal," "Tuckpointing," and "Tuck pointing" were coded as "Tuck pointing" in the harmonized task description variable. A detailed description of the database construction process and the information contained within can be found in Beaudry *et al*. (in press).

Database preparation

The data were selected from records of personal RCS exposure associated with the task-based sampling strategy in the database. Records with missing task descriptions, and those with two or more tasks reported to be performed within the sampling period were excluded. We also excluded measurements made with direct-reading equipment and missing sampling duration. Results from experimental studies investigating the effectiveness of engineering control methods in a laboratory setting were deemed less representative of field conditions and excluded from the analysis.

The original intent of this study was to evaluate the effect of tasks, tools, and materials separately. However, the lack of documentation for tools and materials (for 29 and 25% of the records of the database) and their strong correlation with the task performed prevented their inclusion in the analysis as separate variables. Nevertheless, two task categories were associated with different tools and materials and enough data points to allow for a more refined analysis. Thus, the chipping task was broken down into three categories based on the tools used (jackhammer, other tools, and multiple tools including jackhammer), while the drilling task was separated into three categories based on the material (concrete, rock, and soil and rock).

The initial database contains precise descriptions for the tasks and associated determinants. However, some of the categories had to be grouped to ensure a sufficient sample size for the statistical analysis. Each category had to be associated with a minimum of 10 measurements. Moreover, for categories containing summarized data, the available data had to come from at least two different records. New task categories created include "Foundation tasks not elsewhere classified (n.e.c.)," "Excavation tasks n.e.c.," "Roadwork tasks n.e.c.," and "Masonry tasks n.e.c." For control methods, source isolation and the combination of more than one control method were merged in a new category labeled "other." Industrial and commercial construction sector categories were combined, and the workspace categories were grouped on the basis of work performed either indoors or outdoors. The "other" and "unreported" categories for the construction sector, project type, and source control methods were combined prior to the statistical modeling.

Summarized exposure levels

In order to include both individual and summarized exposure data in the analysis, each set of summary parameters were processed as described in Lavoué *et al*. (2007). First, summarized results not reported as a GM and GSD were transformed to these parameters, assuming a log-normal distribution of the exposure profile. Individual exposures were then simulated from the log-transformed GM and GSD using equation 1, where Z is a random value from the standard normal distribution.

$$x = \exp\left(\ln\left(\mathrm{GM}\right) + \mathrm{Z} \times \ln\left(\mathrm{GSD}\right)\right) \qquad (1)$$

Each summarized record was replaced by a number of simulated exposures equal to the reported sample size, while the associated exposure variables remained unchanged. As an illustration, for a GM and GSD associated with a reported sample size of 10, 10 individual concentrations would be generated and coupled with identical exposure determinants. The simulated data were then combined with the other individual measurements prior to their analysis. Due to the variation inherent to the random simulation procedure, repeating this process yields identical single measurements and different simulated exposure values derived from the summary parameters.

Descriptive statistics

The GM and GSD for each level of categorical determinant listed in Table 1 were computed using robust regression on order statistics (ROS; Helsel, 2005) to account for nondetects. This method applies a linear regression between the detected measurements (following a log-transformation in our analysis) and their normal quantiles in order to model the censored observations. The summary statistics are then computed based on the combined detected and modeled data. The GMs and GSDs were computed using 100 iterations of the simulation procedure, with their median values taken as the final estimate. Variability across the 100 iterations was assessed by computing relative standard deviations (RSD).

Statistical modeling

Statistical modeling was performed using a multimodel averaging approach (Burnham and Anderson, 2002), recently applied in occupational health studies (Lavoué and Droz, 2009). As the name implies, inference in this approach is based on a set of candidate models (the model set), instead of a single "final" model obtained by adding and removing variables. Multimodel inference thus does not assume that a single model is useful, and allows to a certain extent to account for model selection uncertainty (Raftery *et al*., 1997).

The model set was constructed by first creating models containing all possible presence/absence combinations of the variables found in Table 1, as well as sample year and sampling duration. As the main focus of this study was to estimate the effect of tasks and control methods, these two variables were included in all the models. This resulted in a preliminary list of 64 unique model structures. The presence of dilution ventilation in the database was entered as a dichotomous "yes/no" and did not discriminate between mechanical ventilation for interior workspace and the presence of significant wind in exterior settings. An interaction between workspace and ventilation was thus included to account for differences between industrial ventilation indoors and wind outdoors, adding 16 model structures for a final model set size of 80 models.

Table 1. RCS concentrations, proportion of nondetects and measurements derived from summary statistics and median sampling durations by exposure variable.

Variable	*N*	GM[a] (mg m^{-3})	GSD[b]	RSD[c] (%)	ND[d] (%)	SS[e] (%)	Duration[f] (min)
Total	1466	0.050	8.7	3	6	71	334
Task							
Chipping—multiple tools (including jackhammer)	88	0.941	4.7	13	6	93	210
Abrasive blasting	23	0.805	6.3	22	4	61	315
Chipping—jackhammer	56	0.460	2.7	0	7	0	81
Scabbling concrete	12	0.441	3.1	0	50	0	5
Tunnel boring	45	0.328	3.3	12	0	91	390
Tuck pointing	82	0.256	7.7	5	12	12	256
Chipping—other tools	21	0.126	7.4	0	10	0	104
Masonry cutting	81	0.101	4.7	8	5	56	210
Pick and shovel work	11	0.086	2.6	0	9	0	212
Surface grinding/finishing	213	0.071	8.6	6	0	99	309
Moving soil/rock with heavy equipment	13	0.066	4.0	0	8	0	120
Drilling—concrete	45	0.058	10	12	31	36	390
Sanding	31	0.047	7.2	0	42	0	185
Demolition	32	0.032	6.1	36	0	97	334
Drilling—rock	122	0.030	3.9	11	0	98	390
Masonry tasks n.e.c.	14	0.025	4.4	12	0	50	255
Asphalt/concrete road milling	40	0.023	2.8	0	10	0	218
Drilling—soil and rock	13	0.020	6.5	53	15	62	283
Concrete spraying	94	0.018	3.5	12	0	87	390
Roadwork tasks n.e.c.	47	0.018	3.8	9	6	51	350
Installing concrete forms	159	0.015	5.5	9	0	98	390
Electrical maintenance	41	0.013	2.5	13	0	100	390
Concrete/mortar mixing	26	0.012	4.5	13	19	50	336
Cleaning up	15	0.012	3.8	38	0	100	390
Cutting/installing ceiling tiles	42	0.011	7.5	23	45	50	320
Excavation tasks n.e.c.	56	0.010	4.1	17	0	100	341
Foundation tasks n.e.c.	44	0.008	2.9	13	0	100	356
Construction sector							
Residential	35	0.126	5.0	0	37	0	81
Industrial and commercial	161	0.083	8.6	5	19	34	75
Civil engineering and roadwork	838	0.021	5.4	4	3	89	380
Other/unreported	432	0.219	7.8	4	7	55	210
Project type							
Renovation	194	0.072	9.2	2	21	6	221
New construction	823	0.023	5.8	4	1	97	390
Other/unreported	449	0.185	8.2	3	10	51	210
Workspace							
Enclosed/indoors	583	0.042	6.5	4	9	73	390
Open/exterior	670	0.036	9.0	3	5	65	304
Unreported	213	0.231	9.1	7	3	84	210
Ventilation							
No	474	0.204	7.1	3	10	49	185
Yes	535	0.025	6.0	5	1	91	390
Unreported	457	0.027	7.7	5	9	70	324
Controls (source)							
LEV	117	0.092	6.4	4	11	36	90

Table 1. *Continued*

Variable	*N*	GM[a] (mg m^{-3})	GSD[b]	RSD[c] (%)	ND[d] (%)	SS[e] (%)	Duration[f] (min)
Total	1466	0.050	8.7	3	6	71	334
None	726	0.078	9.7	3	3	79	360
Water-fed tool	52	0.071	3.6	5	19	21	204
Manual spraying	100	0.019	4.5	13	6	89	390
Other/unreported	471	0.025	7.4	5	10	68	324

[a]Median value of the geometric mean (GM) with robust regression on order statistics from the 100 iterations.
[b]Median value of the geometric standard deviation (GSD) with regression on order statistics from the 100 iterations.
[c]Relative standard deviation (RSD) of the geometric means across the 100 iterations.
[d]Percentage of values reported as nondetects (ND).
[e]Percentage of values simulated from summary statistics (SS).
[f]Median of the reported sampling duration in minutes.
n.e.c., not elsewhere classified, LEV, local exhaust ventilation

Further data preparation prior to modeling included log-transformation of the RCS concentrations due to the positive skew of their distribution. The sampling duration was also log-transformed and the sampling year was normalized by subtracting the earliest sampling year of the data set. For nominal variables, the categories with the largest sample size were selected as the reference levels.

The relative quality of models in multimodel inference is assessed by the computation of model weights calculated from a goodness-of-fit criterion—in this analysis, a modified Akaike information criterion with a second-order correction (AICc) [equation provided in page 66 of Burnham and Anderson (2002)]. The "Akaike weights" are based on the relative difference in AICc values between each model and the model with the lowest AICc, and add up to 1 (Burnham and Anderson, 2002). Each weight can be seen as the probability of the corresponding model being the best approximating model given the model set and the data. The weights can be used to rank models, quantify the relative importance of explanatory variables through the computation of evidence ratios (Lukacs *et al*., 2007), and estimate averaged model coefficients and predictions. The multimodel coefficients were computed as weighted averages based on the Akaike weights and parameter values across the models in the set, with a value of 0 taken for the coefficients of a variable absent from a model.

The evidence ratios were computed by dividing the sum of the weights of the models containing a variable of interest by the sum of the weights for the models without it. An evidence ratio of 100 or more indicates strong support for a variable being associated with the response. Conversely, an evidence ratio below 0.01 suggests that the variable has little influence on the response (Lukacs *et al*., 2007).

Tobit models (Lubin *et al*., 2004) were used to account for measurements reported as below the limit of detection (LOD). In order to estimate the proportion of variance explained by the full model, a measure frequently reported in modeling studies, the coefficient of determination (R^2) was computed by fitting a linear model containing all the variables and the interaction to the RCS concentrations with nondetects replaced by LOD/2 (Hornung and Reed, 1990). The substitution of nondetects and use of linear model in this instance was due to the lack of consensus on the appropriate method used to estimate the proportion of variance explained with Tobit models (Choodari-Oskooei *et al*., 2012). The modeling procedure was applied to 20 iterations of the simulation procedure to account for the variations related to the imputation of individual exposures from summary statistics. The mean value of the multimodel averaged regression coefficients across the replications was used as the estimate, while the variability between the iterations was assessed by computing the RSD for each coefficient.

Relative indices of exposure (RIE; Lavoué *et al*., 2005) were calculated from the estimated coefficients to illustrate the effects on exposure of the various levels of categorical determinants relative to the reference category. A category with a RIE below 100% is associated with reduced exposure levels compared with the reference category, while a larger RIE indicates the opposite effect.

Exposure levels by task were predicted based on the median sampling year of the data set, and the median sampling duration associated with each task. The exposure scenario developed also assumed an equal distribution of the other reported determinants of exposure—for instance, work being performed 50% indoors and 50% outdoors. As a first exception to this rule, predictions were made by assuming no source control since the different types of control methods were not applicable for some tasks, such as cleaning up or material handling. The other exceptions were for tasks associated only with specific work conditions in the data set. These include asphalt/concrete road milling, other excavation and other foundation for outdoor work and civil engineering construction sector, and tunnel boring for indoor work and civil engineering construction sector.

Data analysis was performed with the R 2.14 software, using the packages NADA (Lee, 2012) to compute descriptive statistics using the ROS method, and survival (Therneau and Lumley, 2012) for Tobit models.

RESULTS

Descriptive statistics

The data set comprised 1466 measurements derived from 480 records and sourced from 46 different publications, encompassing 27 task categories. 430 records were single measurements, including 94 nondetects. The median total GM and GSD over the combined single and simulated data, based on 100 iterations, were 0.050 mg m^{-3} (RSD 3%) and 8.7 (RSD 2%), respectively. The median sampling year of the data set was 1998 (range 1988–2007) and the median sampling duration was 334 min (range 4–734, interquartile interval 210–390). Only 87 measurements (6%) were associated with higher flow (4.2 l min^{-1}) samplers.

The sample sizes, median GMs and GSDs, RSDs of the GMs across the 100 iterations, proportion of nondetects, and simulated values and median sampling duration for each level of the categorical variables are listed in Table 1. The largest median GM for tasks was found for chipping—multiple tools (including jackhammer; 0.941 mg m^{-3}, n = 88), followed by abrasive blasting (0.805 mg m^{-3}, n = 23). The GSDs for the task categories ranged from 2.5 (electrical maintenance) to 10 (drilling—concrete) with a median of 4.4. Four tasks had a median sampling duration of less than 3 h, the shortest being scabbling concrete, with a median of 5 min, followed by chipping—jackhammer with 81 minutes.

The median RSD across the 20 task categories containing individual exposures simulated from summary parameters was 13% (interquartile interval 10–18%), while the RSDs for the other determinants were generally lower with a median of 4%. The three tasks with the largest variation in the estimated GMs between the 100 iterations as assessed by the RSDs were drilling soil and rock (53%), cleaning up (38%), and demolition (36%).

Statistical modeling

The mean percentage of variance explained by the model containing all the variables and the interaction between workspace and ventilation (i.e. the "full" model) was 60% (range 58–62%) across replications, with a mean residual GSD of 3.9 (range 3.8–4.1). In the multimodel approach, the coefficients were based on only two model structures: the full model, with a mean weight of 0.94 across the 20 iterations, followed by the same structure without the project type variable (mean weight of 0.06). Evidence ratios for all variables were very high (above 10^5), with the exception of project type (81). The estimated model parameters averaged across the 20 iterations and their RSDs are presented in Table A1 in the Appendix. The median RSD of the model coefficients was 13% (interquartile interval 8–22%).

Effects of exposure determinants

An increase of 50% in sampling duration (e.g. from 30 to 45 min, or from 2 to 3 h) was associated with a 19% reduction [95% approximate confidence interval (CI) 13–25%] in RCS concentrations. The annual trend consisted of an 11% decrease (95% CI 6–15%) per year in exposure levels. The RIEs for construction sector, project type, and source-based control method categories are presented in Table 2. For the latter, local exhaust ventilation (LEV) (RIE 31%, 95% CI 22–44%) and water-fed tools (RIE 29%, 95% CI 15–54%) were associated with the largest estimated reductions in exposure levels compared with uncontrolled operations.

The interaction between workspace and general ventilation was associated with four combinations (excluding those involving the categories labeled

Table 2. RIE of construction sectors, project types and source control methods.

Variable	RIE (%) (95% CI)
Construction sector	
Residential	127 (57–283)
Industrial and commercial	56 (33–95)
Civil engineering and roadwork	Reference[a]
Project type	
Renovation	91 (55–152)
New construction	Reference
Controls (source)	
LEV	31 (22–44)
None	Reference
Water-fed tool	29 (15–54)
Manual spraying	43 (23–79)

[a]Relative indices of exposure (RIE) of the reference levels taken as 100%. LEV, local exhaust ventilation.

"unreported"), with the combination of outdoors with ventilation (i.e. wind) set as the reference level. The combination of outdoors without wind was associated with a 38-fold increase in exposure levels compared with the reference. The effects for work performed indoors were a 18-fold increase relative to the reference combination of exterior with wind, both with (95% CI 12–26) and without (95% CI 10–33) ventilation.

Estimated exposure levels by task

The estimated exposure levels by task, based on the median duration by category, year 1998 and without source controls are presented in Fig. 1. The largest predicted GMs were found for scabbling concrete (0.728 mg m^{-3}), chipping—multiple tools (including jackhammer; 0.591 mg m^{-3}), and tunnel boring (0.266 mg m^{-3}).

Abrasive blasting (0.191 mg m^{-3}), tuck pointing (0.190 mg m^{-3}), and chipping—jackhammer (0.173 mg m^{-3}) were the other tasks with a mean predicted GM over 0.1 mg m^{-3} based on their median sampling durations. Fifteen of the 27 task categories had an estimated GM under 0.025 mg m^{-3}, including most of the support/ancillary tasks (e.g. material handling and mixing, installing concrete forms, cleaning up, and electrical maintenance).

DISCUSSION

Our study is based on existing exposure data compiled from an extensive literature review, with 27 task categories and 1466 individual task-based exposure measurements. Our data set covered a broader range of construction activities compared with the 16 task categories analyzed by Flanagan *et al*. (2006). The time period covered in our data set was also longer (1988–2007, compared with 1992–2002) and included data from European countries and Canada. We estimate that only 2% of the exposure data is shared between the two studies. The majority of the measurements provided by Flanagan *et al*. were associated with the strategy of evaluating regulatory compliance during the construction of our database. These, along with other measurements comparing exposure levels to occupational exposure limits, were analyzed separately (Sauvé *et al*., 2012). The 27

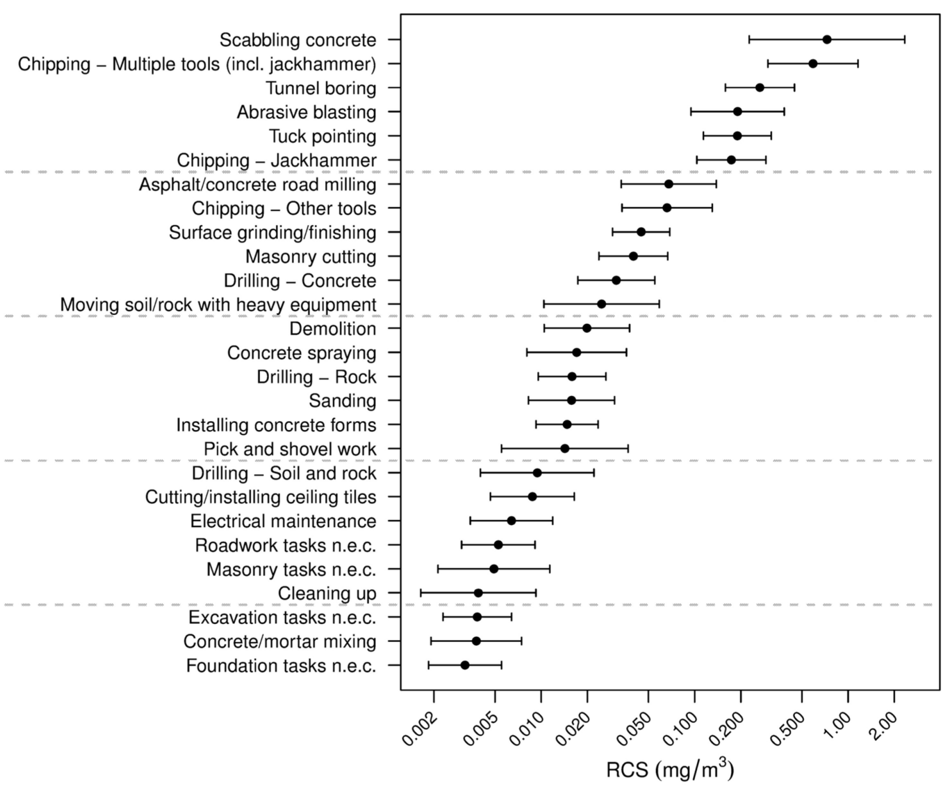

Fig. 1. Estimated geometric mean respirable crystalline silica exposure by task, based on the median sampling duration by task, year 1998 and absence of source controls, averaged across 20 iterations.

tasks categories in our data set encompassed many activities that involves direct disturbance of building materials containing crystalline silica—such as grinding and drilling—and also those of a support nature (e.g. cleaning up and material handling). The range of construction activities covered in our analysis should allow for an improved assessment of work-shift exposures based on the nature and duration of individual tasks.

Descriptive statistics

The total median GM in this study (0.050 mg m^{-3}) was lower than the total GM of the database of Flanagan et al. (2006; 0.13 mg m^{-3}). This is likely due to the large proportion of the data compiled by Flanagan *et al*. being results from legal compliance evaluations, which were excluded from our analysis. Of the three data sources in their database, the measurements from regulatory agencies had the highest GM compared with research or private organizations.

Most tasks in our data set were associated with median sampling times of several hours, which might seem counterintuitive in some cases when considering the time necessary to perform a task only once (e.g. sawing a concrete block). This reflects situations where workers were performing the tasks repeatedly during the sampling period. Our results in these cases therefore represent exposure levels associated with performing a task during part of a shift as opposed to a single task unit.

Regarding the variability associated with the simulation procedure in the estimation of GMs for categorical determinants, the RSDs were generally below 20% for the task categories and 10% for the other determinants. These results are comparable to those reported by Lavoué *et al*. (2007) in their analysis of formaldehyde exposure data from the literature, with a larger proportion of simulated measurements (83 and 85%, compared with 71% in our study) and using 1000 iterations. The variation in the estimated GMs did not appear to be associated with the proportion of measurements derived from summary statistics in the different categories. Our results thus suggest that relatively precise estimates of the GMs can be obtained with 100 replications regardless of the proportion of simulated measurements.

Statistical modeling

The model containing all the variables and the interaction explained an important proportion of the variability in exposure levels with a mean R^2 of 60%, which is comparable to many determinants of exposure studies reviewed by Burstyn and Teschke (1999). Compared with our study, the modeling of the respirable quartz measurements by Flanagan *et al*. (2006) resulted in a R^2 value of 29%, but the final model did not contain the task variable. Our result is more comparable to a determinants of exposure study by Lumens and Spee (2001) investigating four construction trades with models explaining 64 to 82% of the variability in respirable quartz concentrations, depending on the model and population.

The results for the multimodel approach indicated that the computation of model coefficients and predictions were overwhelmingly based on the model containing all the variables (i.e. this model had an Akaike weight very close to 1). This suggests that a simpler, traditional approach (e.g. backward stepwise) to model selection would have yielded similar results, and that the advantages of the multimodel procedure (e.g. integrating the contribution of equally plausible models) are less apparent here. However, we did not know that this would be the case and *post hoc* selection of the modeling approach is generally discouraged (Burnham and Anderson, 2002).

Despite the important proportion of variability explained by the full model, its residual GSD of 3.9 suggests that other factors affecting exposure were unaccounted for in the model. The inclusion of other variables in our analysis—for instance other dust source or use and type of respirators—was considered but ultimately rejected due to too much missing information in the data set. Linear mixed-effect models using publication as a random effect (Berkey *et al*., 1995; Lavoué *et al*., 2007) and substituted nondetects were also investigated but abandoned as the construction sector and source control variables were too closely associated with the publication variable, which gave rise to effects that were difficult to interpret. Similar issues regarding the use of mixed-effect models (with publication as a random effect) were also reported by Hein et al. (2008; 2010) in their analyses of aromatic and chlorinated solvent exposures from the literature.

Effects of exposure determinants

The decrease in exposure levels related to an increase in sampling duration seen in this study was also found in other analyses of existing exposure data (Flanagan *et al*., 2006; Lavoué *et al*., 2007; Park *et al*., 2009). Longer sampling times in low exposure situations can be required to collect sufficient material and ensure a detected result, especially for samplers with lower flow rates, which could explain this association. This effect can also be due to the inclusion of periods with low or no exposure associated with longer sampling times (Kolstad *et al.*, 2005; Lavoué *et al.*, 2006). For example, one study used a pause/stop mode on their sampling train to sample exclusively during the actual concrete grinding (Akbar-Khanzadeh and Brillhart, 2002), while another reported break times within the sampling period (Nash and Williams, 2000). Predictions were made based on the median sampling duration by task, in order to mitigate any potential for misinterpretation of the observed trend.

The 11% per year decrease in exposure levels found in our study is similar to the median annual decrease of 8% per year reported by Symanski *et al.* (1998) based on approximately 700 data sets published between 1967 and 1996. Factors such as technological development and administrative changes have been identified to explain the decreasing exposure levels over time (Kromhout and Vermeulen, 2000). In our case, the trend could be due in part to improvements in dust-suppression efficacy by the different engineering control methods during the period covered by the data set. Flanagan *et al.* (2006) also observed a decreasing trend in RCS exposure levels associated with construction activities within a 10-year range, from a GM of 0.23 mg m^{-3} for 1992–1995 to 0.09 mg m^{-3} for the 1999–2002 period.

The RIEs for the interaction between workspace and ventilation in our study suggest that exposure levels are largely lower in an exterior environment when significant wind is present. This effect was also found in a study conducted on construction sites in Québec (Forest and Tremblay (2007) and by Akbar-Khanzadeh and Brillhart (2002) during concrete finishing, although not statistically significant for the latter. General ventilation indoors had little impact on exposure levels in our study although Akbar-Khanzadeh *et al.* (2010) reported a 66% decrease with ventilation during surface grinding of concrete without any other controls in a field laboratory setup.

The 69 and 71% reductions in RCS exposure levels observed for LEV and water-fed tools were somewhat lower than the efficacy observed in experimental studies, which were excluded from our data set. Studies investigating the effect of tool-based LEV systems on RCS concentrations during tuck pointing, surface grinding, and concrete cutting reported decreased exposure levels from 70 to 99.7% (Croteau *et al.*, 2002; Yasui *et al.*, 2003; Akbar-Khanzadeh *et al.*, 2007; Shepherd *et al.*, 2009). Similarly, water-fed tools reduced exposure levels up to 80–94% during surface grinding (Akbar-Khanzadeh *et al.*, 2010), brick cutting (Beamer *et al.*, 2005), concrete block cutting, and tuck pointing (Echt *et al.*, 2007). The comparable, albeit milder results we found using data from field conditions indicate that engineering control methods are effective in reducing RCS concentrations after accounting for other determinants of exposure.

Estimated exposure levels by task

The distribution of the predicted GMs went in the anticipated direction, with support tasks such as material handling, mixing, and cleanup in the lower tier of Fig. 1, while masonry chipping, abrasive blasting, tunnel boring, and tuck pointing were associated with the largest exposures. The large predicted GM for scabbling concrete is due to its very short duration relative to the other tasks in the data set. While there was a 9-fold difference between the highest and lowest predicted GMs for the chipping tools subcategories, they were all among the tasks with the highest exposures. The contrast in exposure levels was smaller for the drilling subcategories based on materials (3-fold). Material worked on was found to explain the most between-worker variance among the exposure models developed by Tjoe Nij *et al.* (2004) although we did not have sufficient information in the database on repeated measurements to perform such analyses.

Our predictions were lower in most cases than the GMs reported in Table 1. This could be due in part to the exclusion of the effects of the "unreported" levels in the prediction scenario. However, the predictions scenario also excluded the effects of control methods (i.e. only the reference category "none" was considered). The incorporation of control methods would have likely resulted in even lower predicted GMs. While we aimed to predict "global" RCS exposure levels encompassing all possible circumstances contained in the data set, more specific exposure scenarios can be developed for any combination of the determinants using the coefficient values in Table A1.

Study limitations

The variable quality of the information on the contexts and determinants associated with exposure data from the published literature and occupational exposure databases has been identified in several studies (e.g. Burstyn *et al.*, 2000; Flanagan *et al.*, 2006; Gold *et al.*, 2008; Park *et al.*, 2009) and can present a challenge to the data analysis and interpretation of the findings. The percentage of unreported descriptions for the construction sector, project type, workspace, use of ventilation, and control methods variables in our data set ranged from 15 to 31%. Another issue that we encountered in our analysis was the unbalanced distribution of the data across the different categories—for instance, tasks associated with a single tool and material (e.g. tuck point grinding with a tuck point grinder on mortar). We therefore had to adopt a parsimonious approach to the selection of variables included in the models to minimize the potential for multicollinearity, as well as discard more complex statistical analyses such as hierarchical linear models.

Despite the amount of exposure data compiled, some circumstances were less documented in this data set. For instance, support activities (e.g. cleaning up) generally had fewer measurements compared with grinding, drilling, chipping, and cutting, which reflects an emphasis on studying tasks known to be associated with higher exposures. As another illustration, only 35 measurements were associated with the residential sector, which is characterized by smaller firms and has traditionally been less studied (Methner, 2000).

CONCLUSION

In summary, we used exposure data compiled from the literature to estimate RCS concentrations for 27 construction tasks and the effects of the use of engineering control methods and worksite characteristics. The statistical model included in this analysis based on 9 determinants explained an important amount of the variability in exposure levels. This model can be used to predict RCS concentrations for a range of tasks that can be performed during a work shift as part of an exposure assessment program to anticipate, evaluate and control occupational silica hazards in the fleeting and inconsistent environment of construction sites.

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APPENDIX: MULTIMODEL AVERAGED COEFFICIENTS

Table A1. Coefficients from the multimodel inference procedure, averaged over 20 iterations.

Variable	ln RCS (mg m^{-3})		RSD[b] (%)
	β[a]	SE[a]	
Intercept	−1.23	0.569	14
ln[sample duration (min)]	−0.513	0.092	5
Sample year (1988)	−0.112	0.025	11
Task			
Chipping—Multiple tools (including jackhammer)	2.37	0.357	7
Abrasive blasting	1.42	0.380	22
Chipping—jackhammer	0.668	0.312	13
Scabbling concrete	0.667	0.587	23
Tunnel boring	1.25	0.264	12
Tuck pointing	1.35	0.294	8
Chipping—other tools	−0.168	0.365	66
Masonry cutting	−0.315	0.285	34
Pick and shovel work	−1.34	0.498	12
Surface grinding/finishing	Reference		—
Moving soil/rock with heavy equipment	−1.09	0.453	17
Drilling—concrete	−0.270	0.328	99
Sanding	−1.32	0.394	15
Demolition	−0.809	0.295	37
Drilling—rock	−0.921	0.207	18
Masonry tasks n.e.c.	−2.32	0.432	8
Asphalt/concrete road milling	0.656	0.421	19
Drilling—soil and rock	−1.69	0.411	23
Concrete spraying	−0.859	0.328	20
Roadwork tasks n.e.c.	−2.09	0.266	10
Installing concrete forms	−0.996	0.173	13
Electrical maintenance	−1.84	0.273	9
Concrete/mortar mixing	−2.44	0.328	9
Cleaning up	−2.38	0.446	15
Cutting/installing ceiling tiles	−1.64	0.295	19
Excavation tasks n.e.c.	−2.01	0.249	13
Foundation tasks n.e.c.	−2.17	0.267	11
Construction sector			
Residential	0.238	0.409	36
Industrial and commercial	−0.574	0.268	12
Civil engineering and roadwork	Reference		—
Other/unreported	1.74	0.299	9
Project type			
Renovation	−0.093	0.260	107
New construction	Reference		—
Other/unreported	−0.813	0.340	23
Workspace			
Enclosed/indoors	2.87	0.197	5
Open/exterior	Reference		—
Unreported	1.19	1.41	12

Table A1. *Continued*

Variable	ln RCS (mg m^{-3})		RSD[b] (%)
	β[a]	SE[a]	
Ventilation			
No	3.63	0.251	3
Yes	Reference		—
Unreported	2.32	0.408	6
Controls (source)			
LEV	−1.17	0.182	5
None	Reference		—
Water-fed tool	−1.24	0.318	6
Manual spraying	−0.847	0.310	25
Other/unreported	0.140	0.381	63
Workspace: ventilation interaction			
Interior: without ventilation	−3.61	0.303	4
Interior: unreported	−4.10	0.349	4
Unreported: without ventilation	−2.72	1.45	8
Both unreported	−0.971	1.41	15

SE, standard error. RCS, Respirable crystalline silica. n.e.c., not elsewhere classified . LEV, local exhaust ventilation
[a]Average estimated parameter values of the 20 iterations.
[b]Relative standard deviation (RSD) of the model coefficients over the 20 iterations.