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Improving Exposure Estimates by Combining Exposure Information

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Objectives: Any exposure estimation technique has inherent strengths and limitations. In an effort to improve exposure estimates, this study developed and evaluated the performance of several hybrid exposure estimates created by combining information from individual assessment techniques.

Methods: Construction workers (n = 68) each completed three full-shift noise measurements over 4 months. Three single exposure assessment techniques [trade mean (TM), task-based (TB), and subjective rating (SR)] were used to estimate exposures for each subject. Hybrid techniques were then developed which incorporated the TM, SR, and TB noise exposure estimates via arithmetic mean combination, linear regression combination, and modification of TM and TB estimates using SR information. Exposure estimates from the single and hybrid techniques were compared to subjects' measured exposures to evaluate accuracy.

Results: Hybrid estimates generally were more accurate than estimates from single techniques. The best-performing hybrid techniques combined TB and SR estimates and resulted in improvements in estimated exposures compared to single techniques. Hybrid estimates were not improved by the inclusion of TM information in this study.

Conclusions: Hybrid noise exposure estimates performed better than individual estimates, and in this study, combination of TB and SR estimates using linear regression performed best. The application of hybrid approaches in other contexts will depend upon the exposure of interest and the nature of the individual exposure estimates available.

Keywords: data combination; exposure assessment; group mean; hybrid estimate; noise; subjective; task based

INTRODUCTION

Overexposure to noise and subsequent noise-induced hearing loss (NIHL) are common in the construction industry (Suter, 2002). However, there are substantial difficulties involved in evaluating the relationship between noise and NIHL among individual construction workers due to the dynamic nature of exposures in the industry. We previously (Neitzel *et al.*, 2010) compared the performance of three different exposure assessment techniques—a trade-level grouping strategy, a task-based (TB) approach, and subjective rating (SR) of noise—to measured exposures over a 4-month period. Here, we develop and evaluate methods for combining information from the three single techniques to create hybrid exposure estimates intended to reduce measurement error. We then compare the performance of estimates produced using the hybrid techniques to estimates from the single techniques and to measured exposures.

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Background

Minimization of measurement error is important for ensuring accurate estimation of exposure–response relationships (White *et al.*, 2008). Biased estimates, in which assigned exposures differ systematically from true exposures, may result in a shift in the intercept of exposure–response models. This bias alters the effect predicted for any given exposure level (Seixas and Checkoway, 1995) but does not affect the slope estimate of the exposure–response model (Seixas and Sheppard, 1996). Imprecise estimates, in which assigned exposures differ at random from true exposures (i.e. classical measurement error), may result in a reduced estimate of the exposure–response slope (Seixas and Checkoway, 1995).

Individual-level exposure assessment can produce the most precise estimates of long-term average exposure and exposure–response slope coefficients (Heederik and Attfield, 2000), but this approach is sensitive to the information available from each individual, including the number of measurements available per individual (Tielemans *et al.*, 1998; Heederik and Attfield, 2000), with more measurements per individual generally producing more precise and less attenuated slope coefficients (Tielemans *et al.*, 1998; Heederik and Attfield, 2000). An alternative approach involves grouping individuals based on shared characteristics of exposure and assigning each individual the group mean exposure level (Armstrong, 1998). For exposures where dose accumulates linearly, a group-level average is assumed to produce an unbiased estimate of the group mean exposure (Seixas and Sheppard, 1996; Armstrong, 1998). Compared to individual-level assessments, group-based assessments reduce attenuation (Seixas and Sheppard, 1996; Heederik and Attfield, 2000) but increase imprecision (Armstrong, 1998) in exposure–response slope estimates.

Hybrid techniques, which combine information from multiple sources, may ideally capitalize on the strengths of each source and minimize the errors. Hybrid exposure estimates can be created in very simple ways, e.g. the arithmetic mean of various estimates or adjustment of one estimate based on information from another (Semple *et al.*, 2004; Hamra *et al.*, 2008). Approaches such as these are simple and relatively easy to implement but ignore the fact that some measures may be more error prone than others (Seixas and Checkoway, 1995; Teschke *et al.*, 2002). As a result, these relatively straightforward and uncomplicated approaches may have minimal impact on measurement error.

More sophisticated hybrid techniques, such as regression analysis, can assign differing weights to various exposure estimates based on the characteristics of the individual estimates. One potential weakness of hybrid techniques based on regression is that development of predictive models requires a 'gold standard' or measured exposure from which weights for the various estimates of exposure can be derived. Such data are not always available or easily obtained.

Many studies already include multiple assessment techniques on at least of a subset of subjects, but only a few (Seixas and Sheppard, 1996; Schlunssen *et al.*, 2004; McCracken *et al.*, 2009) have combined estimates from multiple techniques to produce hybrid exposure estimates and none appear to have used these techniques to assess noise, one of the most common occupational exposures (NIOSH, 1998). In the current study, we developed several hybrid techniques and compared estimates produced via these techniques to estimates created using single techniques and to measured exposures.

METHODS

Table 1 presents a summary of the abbreviations and metrics discussed in this paper. We have previously described our data collection procedures in a paper which presented a different set of analyses on the same group of subjects (Neitzel *et al.*, 2010). Briefly, we recruited 68 workers from six trades at three large commercial construction sites. All study procedures were approved by the University of Washington Institutional Review Board. We assessed subjects' exposures on three workshifts over 4 months. Subjects completed a survey during each of their three workshifts, which included several SR items concerning subjects' perceptions of their noise exposure. The SR item demonstrating the best association with measured exposures was 'What percent of time are you exposed to each of the following noise levels at work?' with five response categories, which were reduced *post hoc* to three (Neitzel *et al.*, 2009, 2010).

On each of the three measured workshifts, subjects wore a noise dosimeter (Q-300 or NoisePro DLX, Quest Technologies, Oconomowoc, WI). Dosimeters logged the equivalent continuous average level (L_{EQ}) (NIOSH, 1998) at 1-min intervals. During the measured workshifts, subjects also completed an activity card reporting the timing and duration of their tasks.

The performance of exposure estimates is overly optimistic when the estimates are assessed against the same measurement data from which they were generated. For this reason, 'external' data—i.e. levels measured on subjects other than those being

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Table 1. List of abbreviations and exposure measures

Abbreviation	Definition
CV	Cross-validation
R^2	Coefficient of determination
PPE	Personal protective equipment
SD	Standard deviation
SE	Standard error of the mean
SR	Subjective rating of exposure
TB	Task-based exposure
TM	Trade-mean exposure
Measured exposure	
L_{EQi}	Measured mean exposure for an individual worker
Exposure estimates from single techniques	
$L_{EQ,SRi,ext}$	Estimated exposure for an individual worker based on a combination of workers' reported SR exposure and SR noise levels measured at an external site
$L_{EQ,TBi,ext}$	Estimated exposure for an individual worker based on a combination of workers' reported tasks and times at task and task-specific noise levels measured at an external site
$L_{EQ,TMi,ext}$	Estimated exposure for an individual worker based on workers' trade and TM noise levels measured at an external site
Exposure estimates from hybrid techniques	
$L_{EQ,AMi}$	Estimated exposure for an individual worker based on an arithmetic mean combination of that workers' TB, TM, and SR exposure estimates
$L_{EQ,LRi}$	Estimated exposure for an individual worker based on a linear regression prediction of that workers' TB, TM, and SR exposure estimates
$L_{EQ,QTMi}$	Estimated exposure for an individual worker based on a qualitative combination of that workers' TM and SR exposure estimates
$L_{EQ,QTBi}$	Estimated exposure for an individual worker based on a qualitative combination of that workers' TB and SR exposure estimates

studied—were used for estimating exposures in this study. We have previously described (Neitzel *et al.*, 2010) a complementary data set of full-shift L_{EQ}, trade mean (TM) L_{EQ} levels, and task-specific L_{EQ} levels available from subjects at five external construction sites and SR noise levels from subjects at one additional external site. With one exception (described below), the estimates presented here were developed using external trade, task, and SR noise levels.

Data preparation

We checked the dosimetry data for errors and used previously published criteria to remove or correct data (Seixas *et al.*, 2005a). We merged 1-min noise levels with activity card task and survey information to derive TM, TB, and SR noise levels.

Measured exposure levels and estimation of exposures using single assessment techniques

We have described elsewhere (Neitzel *et al.*, 2010) the computation of measured mean exposures (L_{EQi}) across all three measured workshifts for each individual worker$i$, as well as the methods for creating 'external' (*ext*) TM estimates, $L_{EQ,TMi,ext}$; TB estimates, $L_{EQ,TBi,ext}$; and SR estimates, $L_{EQ,SRi,ext}$. These external estimates were based on 64 workers from 5 sites for TM and TB and 19 workers from 1 site for SR. We computed L_{EQi} exposures for each individual as the scaled logarithm of the average of their three measured full-shift exposures; $L_{EQ,TMi,,ext}$, $L_{EQ,TBi,ext}$, and $L_{EQ,SRi,,ext}$ estimates were computed similarly but using estimated, rather than measured, levels (Neitzel *et al.*, 2010). A number of factors which could potentially influence SR perceptions of noise, such as use of hearing protectors and perceived hearing sensitivity, were evaluated previously, and none were found to have a significant impact on the accuracy of the SR estimates (Neitzel *et al.*, 2009, 2010).

Development of hybrid exposure estimates

We developed four hybrid techniques by combining the TM, TB, and SR exposure estimates by calculating an arithmetic mean of the single estimates, by combining the single estimates in a linear regression

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model, and by using SR information to modify both the TM and the TB estimates.

We created an arithmetic mean hybrid estimate for each subject using equation (1):

$$L_{\mathrm{EQ,AM}_i} = \frac{L_{\mathrm{EQ,TM}_{i,\mathrm{ext}}} + L_{\mathrm{EQ,TB}_{i,\mathrm{ext}}} + L_{\mathrm{EQ,SR}_{i,\mathrm{ext}}}}{3}, \quad (1)$$

where $L_{EQ,TMi,ext}$, $L_{EQ,TBi,ext}$, and $L_{EQ,SRi,ext}$ represent the average exposure estimate for individual *i* across that individual's three measured workshifts. $L_{EQ,AMi}$ estimates were created using all possible two- and three-way combinations of TM, TB, and SR estimates (e.g. TM/SR, TB/SR, TM/TB, and TM/TB/SR). We selected this approach because it represents the simplest possible way to combine information from any number and permutation of techniques and because it weights each estimate equally.

We created a linear regression hybrid model using equation (2):

$$L_{\mathrm{EQ}_i} = \alpha + \beta_1\left(L_{\mathrm{EQ,TM}_{i,\mathrm{int}}}\right) + \beta_2\left(L_{\mathrm{EQ,TB}_{i,\mathrm{int}}}\right) + \beta_3\left(L_{\mathrm{EQ,SR}_{i,\mathrm{int}}}\right), \quad (2)$$

where α is the intercept of the regression model and β_1, β_2, and β_3 are regression coefficients for the $L_{EQ,TMi}$, $L_{EQ,TBi}$, and $L_{EQ,SRi}$ estimates, respectively. For the hybrid regression technique only, regression coefficients were developed using the L_{EQi}, TM, TB, and SR noise levels measured on the participating subjects, e.g. the internal noise levels, hence the *int* notation unique to these estimates. Hybrid regression $L_{EQ,LRi}$ exposures were then predicted using these internal regression coefficients and the external TM, TB, and SR noise levels. Thus, we estimated hybrid $L_{EQ,LRi}$ exposures for each individual using noise levels from external sites but subsequently evaluated these estimates against each subject's own measured average exposure. As with the $L_{EQ,AMi}$ technique, we created $L_{EQ,LRi}$ estimates using all possible two- and three-way combinations of the TM, TB, and SR estimates. We selected this approach because it represents a well-understood and stable mechanism for multivariable estimation and because it assigns different data-driven weights to the input variables.

We employed two hybrid qualitative techniques. The first used a combination of the TB and SR estimates across *j* measured workshifts, as shown in equation (3):

$$L_{\mathrm{EQ,QTB}_i} = 10\log_{10}\left[\frac{1}{3}\sum_{j=1}^{3}\left(10^{\left(L_{\mathrm{EQ,TB}_{ij},\mathrm{ext}} + \mathrm{SR}_{\mathrm{Factor},ij}\right)/10}\right)\right], \quad (3)$$

where SR_{Factor} represents an adjustment factor based on subjects' SR responses for each workshift. Based on the approximately 2-dBA steps between noise levels associated with the three response categories of the SR survey item (Neitzel *et al.*, 2010), we assigned the following SR_{Factor} values: +2 dBA for the highest response category ('As loud or louder than a siren'), +0 dBA for the middle category ('Vacuum to chainsaw'), and −2 dBA for the lowest category ('Normal speaking voice or quieter'). Our second qualitative estimate, $L_{EQ,QTMi}$, used a combination of TM and SR estimates by replacing the $L_{EQ,TBij,ext}$ estimates in equation (3) with the $L_{EQ,TMi,ext.}$ These qualitative approaches are superficially similar to the approach shown in equation (1) but employ exponential addition rather than arithmetic averaging within workshift and replace the SR estimate with an *a priori* adjustment factor. We selected these techniques because they can be applied in situations where regression or arithmetic mean approaches may not be feasible (e.g. a single quantitative estimate is available but qualitative SR information are also available or where no measured exposures are available from which prediction models can be developed).

Data analysis

Comparison of estimated to measured exposures. We computed descriptive statistics for the measured mean L_{EQi} exposures and the estimates from the three single and four hybrid techniques. We computed the bias, precision, and accuracy of the estimates using subjects' measured L_{EQi} as the 'true' exposure. Bias was computed as the mean difference between the measured and the estimated exposures (Hornung, 1991), and precision was computed as the standard deviation (SD) of the differences (Hornung, 1991). Accuracy (the average error between the predicted and the measured exposures, also referred to as root-mean-square error) was computed as $\sqrt{(\mathrm{bias})^2 + (\mathrm{precision})^2}$(Hornung, 1991). Smaller bias, precision, and accuracy values indicate better performance. Finally, we regressed estimated exposures from each single and hybrid technique on measured L_{EQi} values and summarized the fraction of variance explained by the estimates using the coefficient of determination (R^2).

Cross-validation of hybrid linear regression models. We used two cross-validation (CV) approaches to evaluate the stability of the predictions made using the hybrid regression technique (Hastie *et al.*, 2009). CV eliminates the optimism in the results that comes from using the same data both for estimation and for prediction. The outcome in both CV approaches was the measured L_{EQi} exposure,

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and the predictor variables were the $L_{EQ,LRi}$ estimates. In the first CV approach (CV_1), we explored the effect of individual subjects on model predictions by randomly dividing the 68 subjects into 10 mutually exclusive groups and creating 'out-of-sample' exposure predictions for each group using only data from the other groups. Between-site variability is a potentially important source of uncontrolled variability, so our second CV approach (CV_2) evaluated the effect of worksite on exposure predictions by dividing subjects into three groups based on site and again creating out-of-sample predictions for each group. For both the CV_1 and CV_2 approaches, we computed accuracy and R^2 for the predicted values and compared the results to the optimistic estimates of these quantities developed using naive model assessment.

RESULTS

Comparison of estimated and measured exposures

Table 2 shows descriptive statistics for the measured exposures and exposure estimates from the various single and hybrid techniques. The measured L_{EQi} for the 68 subjects was 89.6 ± 3.4 dBA, and 61 workers (90%) had L_{EQi} levels, which equaled or exceeded the recommended 85-dBA limit (NIOSH, 1998). Mean exposure estimates from the various techniques were similar, with a 3.8-dBA overall range. The SDs of the estimates indicated a loss of exposure variability—by as much as two-thirds, in some cases—when compared to the SDs of the measured exposures. Among the single techniques, the $L_{EQ,TBi}$ estimates had the largest SD; the regression and qualitative TB/SR hybrid estimates showed even larger variability. Among the single techniques, the TB estimates generally showed the best bias, precision, and accuracy and the TM estimates showed the worst. Hybrid estimates almost uniformly resulted in improvements in precision over the single techniques and generally also showed improved accuracy, even though some of the hybrid techniques showed similar or greater bias. Hybrid estimates which did not include TM data performed better than any of the single techniques, and hybrid estimates which included TM data performed better than the single TM technique and in some cases better than the other two single techniques, as well. The hybrid two-way arithmetic mean and regression

Table 2. Mean and SD of measured and estimated exposures and error in estimated compared to measured exposures (n = 68 subjects)

	Noise exposure level (dBA)[a]		Performance measure			
Exposure measure	Mean	SD	Bias (dBA)	Precision (dBA)	Accuracy (dBA)	R^2 with L_{EQi}
Measured mean L_{EQi}	89.6	3.4	—	—	—	—
Estimates from single techniques						
$L_{EQ,TMi,ext}$	88.5	2.0	−1.1	3.8	4.0	0.03
$L_{EQ,TBi,ext}$	89.1	2.5	−0.5	3.1	3.1	0.26
$L_{EQ,SRi,ext}$	91.8	1.0	2.2	3.0	3.7	0.42
Estimates from hybrid techniques						
$L_{EQ,AMi}$						
TM/TB/SR	89.8	1.4	0.2	3.1	3.1	0.27
TB/SR	90.4	1.5	0.9	2.8	2.9	0.42
TM/SR	90.1	1.2	−0.6	3.3	3.3	0.18
TM/TB	88.8	2.0	0.8	3.3	3.3	0.17
$L_{EQ,LRi}$						
TM/TB/SR	89.7	2.6	0.1	2.4	2.4	0.55
TB/SR	89.7	2.6	0.1	2.4	2.4	0.54
TM/SR	89.9	2.4	0.3	2.7	2.7	0.43
TM/TB	89.2	1.9	−0.4	3.0	3.0	0.35
$L_{EQ,QTMi}$	88.0	2.4	−1.5	3.3	3.6	0.19
$L_{EQ,QTBi}$	88.7	3.1	−0.9	2.8	2.9	0.44

$L_{EQ,AMi}$, hybrid arithmetic mean combination of TB estimate and SR information; $L_{EQ,LRi}$, hybrid regression combination of TB estimate and SR information; $L_{EQ,QTMi}$, hybrid qualitative combination of TM estimate and SR information; $L_{EQ,QTBi}$, hybrid qualitative combination of TB estimate and SR information.
[a]For a full description of the creation of TM, TB, and SR estimates, see Neitzel *et al.* (2010).

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combinations with the highest R^2 values after regression on the measured L_{EQi} levels were both TB/SR combinations; these combinations were therefore selected for full analysis.

The distribution of estimated compared to measured exposures varied by technique (Fig. 1), with the $L_{EQ,TMi}$ estimates showing the most pronounced deviations between best fit and perfect agreement lines. The pronounced deviation in the $L_{EQ,TMi}$ estimates is at least partly due to the individuals with the lowest and highest TM exposure estimates. The individuals with the lowest TM levels were all electricians from a single internal site, and the TM for electricians at this site was 4.4 dBA higher than that

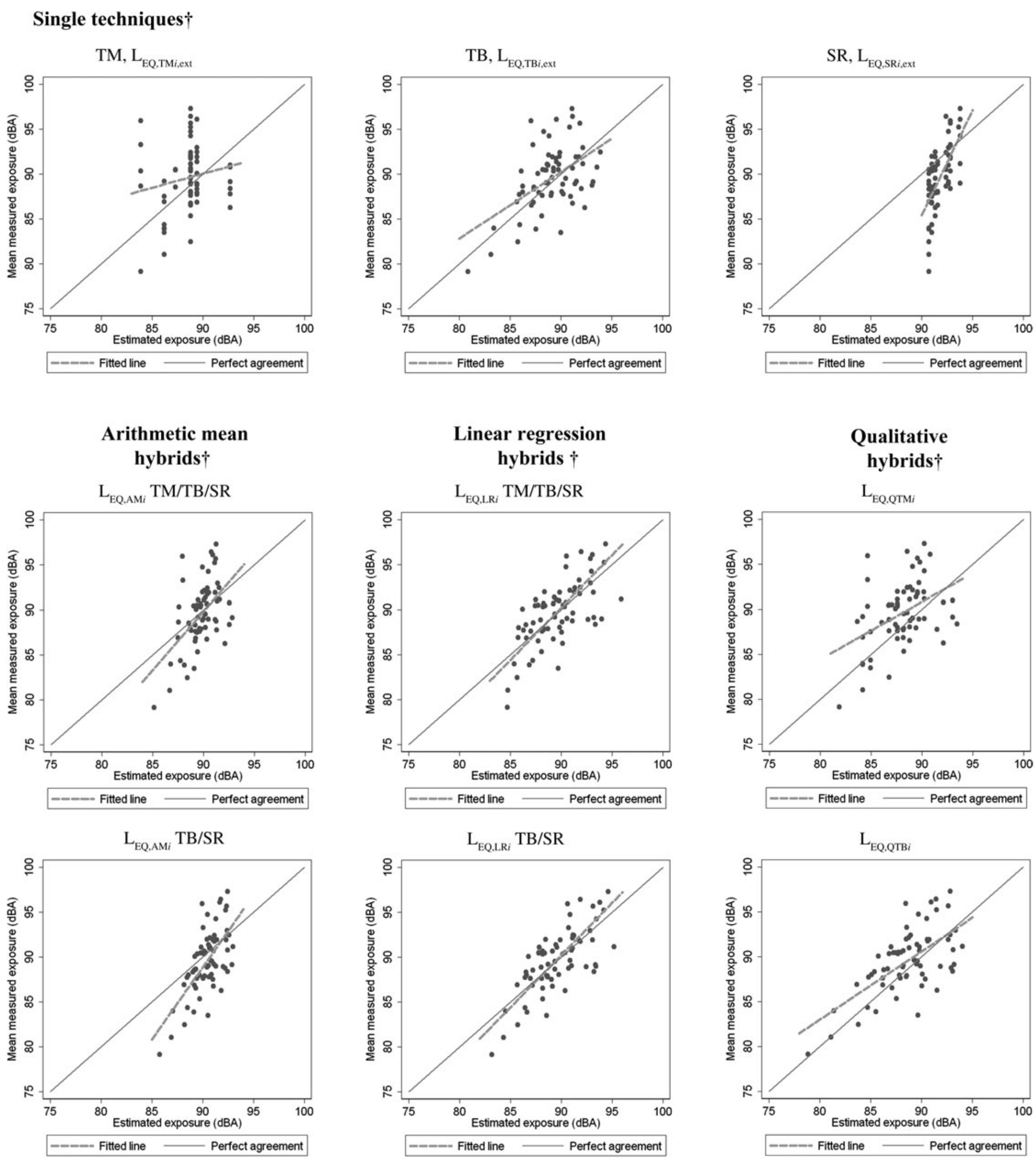

Fig. 1. Measured versus estimated exposures† (n = 68 subjects † See (Neitzel et al., 2010) for a full description of the creation of TM, TB, and SR estimates). TM = trade-mean; TB = task-based; SR = subjective rating; $L_{EQ,\ AMi}$= hybrid arithmetic mean combination of TB estimate and SR information; $L_{EQ,\ LRi}$= hybrid regression combination of TB estimate and SR information; $L_{EQ,\ QTMi}$= hybrid qualitative combination of TM estimate and SR information; $L_{EQ,\ QTBi}$= hybrid qualitative combination of TB estimate and SR information.

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of the two electricians from the two external sites where electricians were employed. This resulted in substantially underestimated TM exposures for these workers. The opposite situation was encountered for the individuals with the highest TM levels, who were ironworkers from two internal sites. Their TM level was 4.4 dBA lower than that of the single external site which included ironworkers, which resulted in substantially overestimated TM exposures for these workers. The $L_{EQ,LRi}$ (TM/TB/SR), $L_{EQ,LRi}$ (TB/SR), and $L_{EQ,AMi}$ (TB/SR) estimates showed the greatest similarities between the fitted and the perfect agreement lines, the greatest range of estimated values in comparison to measured exposures, and the closest rank ordering of measured and estimated exposures. Estimates from the other techniques showed greater scatter from the perfect agreement line, marked slope attenuation (for $L_{EQ,TMi}$ and $L_{EQ,QTMi}$), and inflated slope estimates [for $L_{EQ,SRi}$, due to the fact that the SR noise levels used to create these estimates came from a particularly noisy site (Neitzel *et al.*, 2010)].

Overall, the results in Table 2 and Fig. 1 indicate that the hybrid regression TM/TB/SR and TB/SR techniques had the best performance of all techniques. These regression results are overstated because the weights are derived from the same data on which they are evaluated. Thus, it is noteworthy that the performance of the simpler arithmetic mean TB/SR and qualitative TB/SR techniques was only slightly worse.

Table 3 shows linear regression coefficients and associated standard errors (SEs) for single and two- and three-way combination hybrid regression estimates. For both the single techniques and the hybrid combinations, the coefficients associated with the TM estimates were lowest (essentially zero) and alternated between positive and negative. The TM SEs were also consistently the largest relative to coefficient size, indicating that the TM coefficients had the greatest associated error. In the hybrid techniques combining TM, TB, and SR estimates, the regression coefficient assigned to the TM estimates had a small negative and non-significant coefficient. The hybrid coefficients for the TB and SR estimates, as well as the R^2 values (Table 2), were similar whether or not the techniques included TM estimates.

CV of hybrid regression models

CV results for the regression hybrid models are shown in Table 4, and Fig. 2 displays scatterplots of measured exposures versus hybrid TM/TB/SR regression estimates made using the naive and CV approaches. The CV_1 approach, which randomly excluded subjects, showed only modest decrements in model fit (R^2) and accuracy when compared to the naive model. The CV_2 results, which randomly excluded sites, differed little from the naive model for the TB/SR model. However, the TM/TB/SR CV_2 results showed substantially reduced performance compared to the naive model, with a 30% reduction in precision and accuracy (data not shown), marked deviation of the fitted from the perfect agreement line, increased scatter, and slope attenuation (Fig. 2).

Further exploration of potential causes of the reduced performance of the TM/TB/SR CV_2 analysis indicated that the substantial reduction in model fit and increased variability in model coefficients were related to unequal distribution of trades across the internal sites (from which the hybrid regression coefficients were developed) and the external sites (from which TM, TB, and SR noise levels used to create hybrid regression predictions were drawn). Two trades (carpenters and laborers) were present at all

Table 3. Regression coefficients for prediction models for single and hybrid techniques

$L_{EQ,LRi}$ model	Regression coefficients (β)			
	α (SE)	TM[a] (SE)	TB[a] (SE)	SR[a] (SE)
Estimates from single techniques				
TM	61.9 (19.1)	0.3 (0.2)		
TB	23.5 (13.6)		0.7 (0.2)	
SR	−125.0 (31.2)			2.3 (0.3)
Estimates from hybrid techniques				
TM/TB/SR	−124.1 (30.3)	−0.2 (0.2)	0.6 (0.2)	1.9 (0.3)
TB/SR	−137.4 (28.2)		0.5 (0.1)	2.0 (0.3)
TM/SR	−140.6 (33.3)	0.2 (0.2)		2.3 (0.3)
TM/TB	38.8 (17.7)	−0.3 (0.2)	0.9 (0.2)	

β, regression coefficients; $L_{EQ,LRi}$, hybrid regression combination of TB estimate and SR information; α, model intercept.
[a]For a full description of the creation of TM, TB, and SR estimates, see Neitzel *et al.* (2010).

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internal and external sites, but workers at the majority of internal and external sites represented three or fewer of the six trades assessed. Large differences (4 dBA or more) in TM levels for the trades represented by only a few internal and external measurements (electricians and ironworkers) further contributed to model instability and to poor performance of the TM estimates in general.

DISCUSSION

We estimated noise exposures using hybrid combinations of estimates developed using TM, TB, and SR techniques and compared these estimates to those from the single techniques, as well as to measured exposures. The hybrid estimates generally showed appreciable improvements in accuracy compared to the single TM, TB, and SR techniques. In particular, linear regression combination of TB and SR estimates and modification of the TB estimates based on SR information demonstrated moderate to substantial improvements in performance over the single techniques. The hybrid regression approach had the best performance overall, even after CV. This result is not especially surprising given the general utility of regression analysis. The fact that the performance of the much simpler combining of TB and SR information approached that of the regression technique was surprising.

Our results generally agree with the exposure assessment features of the few previous epidemiological studies which have explored the use of hybrid techniques. Hoek *et al.* (2001) estimated individual-level air pollutant concentrations by summing the contributions of regional background concentrations, urban measurements, and local traffic intensity and found that this hybrid approach resulted in substantially increased contrast in estimated exposures across the study region compared to a non-hybrid approach. Isakov *et al.* (2007, 2009) combined regional grid models and local dispersion models to estimate community exposures to air pollutants and found that the hybrid technique resulted in a several-fold difference in local exposure estimates compared to the regional grid model alone. Seixas and Sheppard (1996) used the James–Stein shrinkage estimator to weight simulated group and individual mean levels and found that this hybrid approach reduced the attenuation bias of individual mean exposure estimates while also improving the precision of the group mean estimates. Schlunssen *et al.* (2004) demonstrated that a weighted combination of individual- and group-level wood dust

Table 4. Accuracy and model fit of full data set and CV of hybrid $L_{EQ,LRi}$ models based on randomly excluded subjects (CV_1) and excluded sites (CV_2) compared to measured exposure levels (n = 68 subjects)

$L_{EQ,Ri}$ model	Accuracy (dBA)	R^2
TM/TB/SR[a]		
Naive model	2.4	0.55
CV_1	2.7	0.45
CV_2	3.5	0.18
TB/SR[a]		
Naive model	2.4	0.54
CV_1	2.6	0.46
CV_2	2.7	0.44

$L_{EQ,LRi}$, hybrid regression combination of TB estimate and SR information; CV_1, CV based on randomly excluded subjects; CV_2, CV based on excluded sites.
[a]For a full description of the creation of TM, TB, and SR estimates, see Neitzel *et al.* (2010).

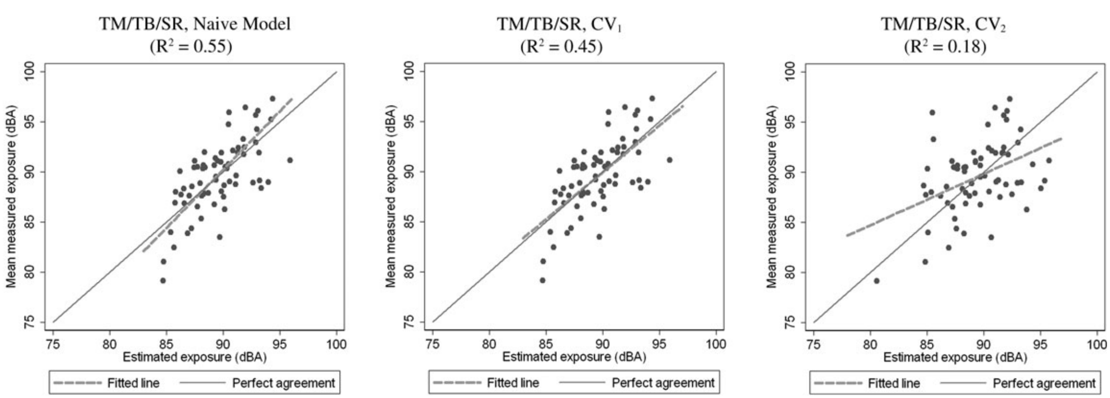

Fig. 2. Naive model and CV hybrid regression $L_{EQ,LRi}$ TM/TB/SR estimates based on randomly excluded subjects (CV_1) and excluded sites (CV_2) compared to measured exposure levels (n = 68 subjects). † R^2 values are from models regressing estimated exposures on measured exposures. TM = trade-mean, TB = task-based, SR = subjective rating; CV_1 = cross-validation based on randomly-excluded subjects; CV_2 = cross-validation based on excluded sites.

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exposure information estimated using the James–Stein shrinkage estimator produced an exposure–response slope coefficient that was much larger than that of individual-level measurements and more precise than the group-level estimates.

Bayesian approaches represent a probabilistic technique for synthesizing exposure information from different sources—in the occupational exposure literature, typically subjective expert ratings and measured exposure levels (Ramachandran, 2001; Hewett *et al.*, 2006). Bayesian approaches were not appropriate for combining exposure estimates in the current study for several reasons. First, the estimates from the assessment techniques were not independent from the measurement data (Wild *et al.*, 2002). Second, Bayesian methods are most useful where measurement data are sparse (Ramachandran and Vincent, 1999), which was not the case given the rich exposure data set in the current study. Third, unlike SRs by experts, for which rater uncertainty can be assessed across multiple exposure estimates per rater (Ramachandran *et al.*, 2003), the worker SR technique used here resulted in one exposure estimate per rater, with no definable bounds on rater uncertainty. Finally, the goal of the study was to combine information from three exposure assessment techniques simultaneously, and it is unclear how this could have been accomplished within the Bayesian framework. The results of this study could be used to define priors for future Bayesian exposure assessments in similar populations.

Inclusion of TM estimates in the hybrid techniques generally did not improve the performance of estimated exposures and in the arithmetic mean estimates developed using TM, TB, and SR estimates actually reduced performance. The poor performance associated with hybrid techniques which incorporated TM data is consistent with our previous analysis of the TM technique using the same data set (Neitzel *et al.*, 2010). Although TM assessment has been widely applied in the construction exposure literature and although previous studies have demonstrated that group-based approaches reduce measurement error (Tielemans *et al.*, 1998; Heederik and Attfield, 2000), techniques which downweighted or eliminated TM estimates generally performed best here. This study was limited by the small number of sites and workers and by unequal distributions of trades across sites. Our CV results based on leaving out one site at a time suggest that differences in noise exposure between sites became confounded with TM estimates in our study. Thus, we found that the hybrid techniques including only TB and SR information produced more stable estimates than those which also incorporated TM levels. As we have noted previously (Neitzel *et al.*, 2010), in small studies where the rank ordering of TM levels varies markedly across study sites, and the distribution of trades is not balanced across sites, the utility of the TM approach is severely reduced.

As with any modeling exercise, the current study had a number of limitations, some of which we have discussed in detail previously (Neitzel *et al.*, 2010). First, treatment of three measured full-shift exposures over a 4-month period as a worker's 'true' exposure level ignores the fact that the measured exposures are a highly uncertain estimate of the 4-month average exposure. Second, lack of an external set of study sites with a complete data set of measured exposures and TM, TB, and SR data hampered our ability to externally validate the performance of all techniques equally well. Third, the results of the CV analyses show the importance of site-to-site variability in construction and most notably in our case when considering TM exposures. Unfortunately, while these effects are important, the transient nature of construction work generally limits the potential inclusion of site-specific effects into exposure assessment models. This finding does highlight the importance of collecting trade-specific data across multiple sites to limit the influence of measurements from a particular site. Finally, the small number of subjects and sites evaluated here may substantially reduce the generalizability of the current results.

The majority of the hybrid techniques we evaluated performed better than the single techniques, which represent traditional approaches to exposure assessment. The hybrid linear regression technique combining TB and SR estimates had the best performance of any of the techniques evaluated here and showed reasonably good stability and consistent performance under CV. This suggests that there is added value in collecting subjective information on noise exposure to addition to information on workers' specific activities, as perceptions of exposure line up well with actual exposures and provide additional information not easily obtained through standard occupational exposure assessment tools. This finding supports previous studies which have demonstrated the value of subjective information in assessing exposures to noise (Ising *et al.*, 1997; Ahmed *et al.*, 2004; Schlaefer *et al.*, 2009), as well as to dust (Fonn *et al.*, 1993; Nieuwenhuijsen *et al.*, 1997) and ergonomic hazards (Buchholz *et al.*, 2008).

Our characterization of the exposure–response relationship between noise and NIHL may be improved further if use of personal protective equipment (PPE) can be integrated into hybrid estimates

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of exposure. The importance of accounting for use of PPE in occupational epidemiological studies has been demonstrated in recent studies (Seixas *et al.*, 2004, 2005b; Davies *et al.*, 2009; Sbihi *et al.*, 2010). Hearing protector use is not common in construction in the USA (Suter, 2002; Neitzel and Seixas, 2005), but failure to account for the reduction in exposure afforded to those workers who do use protectors introduces additional but potentially avoidable measurement error.

The results of this study provide useful guidance for estimation of exposure to highly variable noise. While we have not assessed the epidemiological properties of hybrid techniques in this paper, use of such techniques in future analyses of construction noise and NIHL, along with integration of hearing protector use, should result in better estimates of exposure–response relationships. These techniques may also prove useful in analyses of other exposures in different settings, provided that multiple sources of exposure data are available. Many studies, particularly those in nutritional epidemiology, already include multiple assessment techniques for validation purposes (Brunner *et al.*, 2001; Kabagambe *et al.*, 2001; Schatzkin *et al.*, 2003; Andersen *et al.*, 2005; Shai *et al.*, 2005; Rosner *et al.*, 2008), and the combination of these data streams into hybrid estimates is the logical next step in exposure assessment. Further validation of the hybrid techniques developed here is required before these techniques can be applied to studies of other exposures.

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