Development of a source-exposure matrix for occupational exposure assessment of electromagnetic fields in the INTEROCC study

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Abbreviated title: An EMF source-exposure matrix

Word count - Abstract: 213
Word count - Main text: 4 908
Total number of tables and figures: 8

Financial support: This work was funded by the National Institutes for Health (NIH) Grant No. 1R01CA124759-01. Coding of the French occupational data was in part funded by AFSSET (Convention N° ST-2005-004). The INTERPHONE study was supported by funding from the European Fifth Framework Program, 'Quality of Life and Management of Living Resources' (contract 100 QLK4-CT-1999901563) and the International Union against Cancer (UICC). The UICC received funds for this purpose from the Mobile Manufacturers' Forum and GSM Association. Provision of funds to the INTERPHONE study investigators via the UICC was governed by agreements that guaranteed INTERPHONE's complete scientific independence (http://interphone.iarc.fr/interphone_funding.php). In Australia, funding was received from the Australian National Health and Medical Research 5 Council (EME Grant 219129) with funds originally derived from mobile phone service licence fees; a University of Sydney Medical Foundation Program; the Cancer Council NSW and The Cancer Council Victoria. In Montreal, Canada, funding was received from the Canadian Institutes of Health Research (project MOP-42525); the Canada Research Chair programme; the Guzzo-CRS Chair in Environment and Cancer; the Fonds de la recherche en sante du Quebec; the Société de recherché sur le cancer; in Ottawa and Vancouver, Canada, from the Canadian Institutes of Health Research (CIHR), the latter including partial support from the Canadian Wireless Telecommunications Association; the NSERC/SSHRC/McLaughlin Chair in Population Health Risk Assessment at the University of Ottawa. In France, funding was received by l'Association pour la Recherche sur le Cancer (ARC) (Contrat N85142) and three network operators (Orange, SFR, Bouygues Telecom). In Germany, funding was received from the German Mobile Phone Research Program (Deutsches Mobilfunkforschungsprogramm) of the German Federal Ministry for the Environment, Nuclear 45 Safety, and Nature Protection; the Ministry for the Environment and Traffic of the state of Baden- Wurttemberg; the Ministry for the Environment of the state of North Rhine-Westphalia; the MAIFOR Program (Mainzer Forschungsforderungsprogramm) of the University of Mainz. In New Zealand, funding was provided by the Health Research Council, Hawkes Bay Medical Research Foundation, the Wellington Medical Research Foundation, the Waikato Medical Research Foundation and the Cancer Society of New Zealand. Additional funding for the UK study was received from the Mobile Telecommunications, Health and Research (MTHR) program, funding from the Health and Safety Executive, the Department of Health, the UK Network Operators (O2, Orange, T-Mobile, Vodafone, '3') and the Scottish Executive. All industry funding was governed by contracts guaranteeing the complete scientific independence of the investigators.

Conflict of interest: The authors have no conflicts of interest to declare.

GLOSSARY

EMF: Electromagnetic fields

E-field: Electric field strength, in volts per meter (V/m)

H-field: Magnetic field strength, in amperes per meter (A/m) [high frequency fields]

B-field: Magnetic flux density, in microTesla (µT) [low frequency fields]

PD: Power Density, in watts per square meter (W/m^2)

SMF: Static Magnetic Fields, in microTesla (µT), 0 Hz

ELF: Extremely Low Frequency (3-3000 Hz)

IF: Intermediate Frequency (3 kHz – 10 MHz)

RF: Radiofrequency (10 MHz – 300 GHz)

Min: Minimum

Max: Maximum

N: Sample size

AM: Arithmetic mean

GM: Geometric mean

SD: Standard deviation

GSD: Geometric standard deviation

z_{Max}: Standard normal quantile of a data set's maximum value

ODR: Outside Dynamic Range (The range between an EMF instrument's overload input and its minimum input with acceptable accuracy)

HVTL: High Voltage Transmission Lines

TIG: Tungsten Inert Gas

CVD: Chemical Vapor Deposition

ABSTRACT

Introduction: To estimate occupational exposures to electromagnetic fields (EMF) for the INTEROCC study, a database of source-based measurements extracted from published and unpublished literature resources had been previously constructed. The aim of the current work was to summarize these measurements into a source-exposure matrix (SEM), accounting for their quality and relevance. **Methods:** A novel methodology for combining available measurements was developed, based on order statistics and log-normal distribution characteristics. Arithmetic and geometric means, and estimates of variability and maximum exposure were calculated by EMF source, frequency band and dosimetry type. Mean estimates were weighted by our confidence in the pooled measurements. **Results:** The SEM contains confidence-weighted mean and maximum estimates for 312 EMF exposure sources (from 0 Hz to 300 GHz). Operator position geometric mean electric field levels for RF sources ranged between 0.8 V/m (plasma etcher) and 320 V/m (RF sealer), while magnetic fields ranged from 0.02 A/m (speed radar) to 0.6 A/m (microwave heating). For ELF sources, electric fields ranged between 0.2 V/m (electric forklift) and 11,700 V/m (HVTL-hotsticks), while magnetic fields ranged between 0.14 µT (visual display terminals) and 17 µT (TIG welding). **Conclusion:** The methodology developed allowed the construction of the first EMF-SEM and may be used to summarize similar exposure data for other physical or chemical agents.

Keywords: source-exposure matrix, electromagnetic fields, occupational exposure assessment, log-normal distribution, semi-empirical exposure estimation

INTRODUCTION

Population-based case-control studies require the use of retrospective exposure assessment tools based on quality historical exposure data. However, the collection and analysis of these data is difficult, since measurements for some environmental and occupational agents, such as electromagnetic fields (EMF), are not systematically collected and, when available, are almost exclusively reported as aggregated and summarized results. Past efforts analysed and combined available exposure data in the literature for different agents[1–8]. They involved estimation of specific parameters from scarce measurements, using a limited number of equations based on the assumption of data log-normality. Monte-Carlo simulations[1,2,7] were also used to recreate exposures when measurement data were sparse.

Measurements collected from the literature have been used in the construction of job-exposure matrices (JEMs), either alone or in combination with expert judgments. For EMF, JEMs have been created only for extremely low frequency (ELF) magnetic fields[9–12] and electric shocks[13,14]. However, a worker´s job title is insufficient to explain between-subject variability since exposure levels are influenced by other characteristics, such as industry, worker's tasks, specific equipment used or physical configuration of the workplace[15,16]. The JEM´s mean of exposure measurements from a sample of workers with the same occupation introduces Berkson errors in the exposure estimate for a given individual, reducing the study´s power to detect true hazards[17] and potentially biasing risk estimates[18].

Some authors[16] suggested the use of source-based measurements and questionnaires to improve EMF exposure assessment, allowing for a more individualized exposure estimation.

The INTEROCC EMF measurement database

As part of the INTEROCC/INTERPHONE study of brain cancer, detailed information was collected for each job held by the study participants through a questionnaire on work organization (e.g. manual/automated), tasks (e.g. welding) and sources of exposure (e.g. type of equipment), divided in twelve occupational sections to take industrial activity into account. The aim was to combine the interview data and EMF exposure measurements from the literature for each source and/or task to estimate individual cumulative exposures to electric fields (E) and magnetic fields (B for lower frequencies and H for higher frequencies) in four frequency bands: 0 Hz for static magnetic fields (SMF), 3–3,000 Hz for extremely low frequencies (ELF), 3 kHz – 10 MHz for intermediate frequencies (IF) and 10 MHz – 300 GHz for radio frequencies (RF).

Measurements for all the EMF sources identified through the study questionnaire (over 3 000 records) were compiled into an occupational exposure measurement database (OEMD). The measurements collected were abstracted from published and unpublished resources (i.e. 95 articles and technical reports), which were assessed based on their quality and relevance for our study. The OEMD was augmented with estimates of exposure range for 39 RF sources without available measurements in the literature, obtained from expert judgments. In total, exposures were compiled for 312 EMF sources commonly found in workplaces, covering the entire EMF frequency range. In this database, an EMF source refers to a specific piece of equipment and/or task which can lead to EMF exposure. Details of the construction and content of the OEMD were recently published[19] and public access to this database is available at www.crealradiation.com/index.php/en/databases.

EMF data are usually reported using a variety of summary statistics, from arithmetic and geometric means (*AM* & *GM*), minimum (*Min*) and maximum (*Max*), only maximum, or values below or above the EMF meter's limits of detection (i.e. outside its dynamic range or ODR). Several dosimetry types can be used when sampling EMF (i.e. personal, operator position or spot). Personal measurements are obtained with dosimeters by collecting exposures over an hour, a shift, or longer. Spot measurements are made at different distances from the source over shorter periods of time. Spot measurements performed at the usual worker´s position are called "operator position" measurements[20]. The analysis and combination of these data entail several difficulties, as highlighted in similar efforts[3,4,7]. Since measurements are collected for different purposes and following different sampling strategies, quality and relevance for epidemiological studies also needs to be considered.

The aim of this article is to describe the methodology developed to combine the OEMD data into a source-exposure matrix (SEM), containing representative exposure estimates and their within-source variability for all EMF sources identified in the INTEROCC study.

METHODS

The methodology developed has two main stages: 1) calculation of semi-empiric estimates of missing summary statistics in OEMD studies; and 2) pooling of reported and/or estimated summary statistics. Pooled statistics were weighted by semi-quantitative ratings from expert confidence evaluations that a study's measurement data are accurate and representative of long-term brain exposure.

Semi-empirical methods for estimating missing summary statistics

Each OEMD record for a given EMF source may contain values for combinations of *Min, Max*, *AM, GM, N* (sample size) and the minimum or maximum ODR limit for a specific frequency band and dosimetry type. To construct the SEM, we estimated *AM*, *GM*, *SD* and *GSD* for all EMF sources using these varied information. Our approach assumed that EMF exposure, like other environmental and occupational agents[21–23], is log-normally distributed. The summary statistics from log-normal data obey several mathematical relationships (see Appendix), including this equation for the standard normal quantile *z* of the maximum data point:

$$z_{Max} = \frac{\ln Max - \ln GM}{\ln GSD} \qquad (1)$$

and the analogous equation for z_{Min}. Our second assumption was that z_{Max} and z_{Min} are symmetric about zero:

$$z_{Max} = - z_{Min} \qquad (2)$$

Equation 1 and other relationships[24] between the summary statistics *AM, SD, GM, GSD,* of a log-normal distribution, and parameters z_{Max}*, Min* and *Max*, were used to derive estimation formulas for missing statistics, depending on available values in the OEMD (Table 1). For OEMD records with values for *N* (22% of the total), we further assumed that z_{Min} and z_{Max} were equal to their expected normal order statistics[25,26], which we call $E_N[z_{Min}]$ and $E_N[z_{Max}]$, since the expectation values of the extreme normal quantiles also have the symmetric quantile property[22].

With values for $E_N[z_{Max}]$ obtained from a numerical algorithm[25], these log-normal relationships could be solved exactly to obtain all summary statistics for OEMD records with 3 or more parameter values (estimation methods 1 and 2 in Table 1). When less information was available, solutions for the desired summary statistics were made possible by replacing the unknown *GSD* with its central tendency, $\overline{GSD}$, calculated from an OEMD sub-set with enough data for exact calculations using these two methods. This semi-empiric parameter plus the above approximations resulted in the formulas for estimation methods 3 – 5 in Table 1. For OEMD records without *N*, we replaced $E_N[z_{Max}]$ with a semi-empiric parameter, $\overline{z_{Max}}$, which equals the central tendency of $E_N[z_{Max}]$ from all OEMD records with values for *N*. With this substitution plus the symmetric quantile relationship (eq.2), formulas similar to those in Table 1 were derived (see Appendix). OEMD records with N=1 (i.e. single measurements) were considered to equal their *AM* and *GM,* while *SD* and *GSD* are undetermined.

When ODR measurements were reported, providing their corresponding limits of detection, they were entered into OEMD as ODR*Min* or ODR*Max,* with the corresponding *Max* or *Min*. For these entries, we estimated the desired statistics with models for the extreme exposures outside the dynamic range:

$$Min = ODRMin * k_{under} \tag{3a}$$

$$Max = ODRMax * k_{over} \tag{3b}$$

The correction factors k_{under} and k_{over} were estimated semi-empirically from a sub-set of ODR measurements that also reported the *AM*, so that:

$$k_{under} = \frac{AM^2}{Max * ODRMin * \sqrt{Q}} \tag{4a}$$

$$k_{over} = \frac{AM^2}{Min * ODRMax * \sqrt{Q}} \tag{4b}$$

where the parameter $Q = \overline{GSD}^{\ln \overline{GSD}}$ uses the central tendency $\overline{GSD}$, previously described. The central tendencies $\overline{k_{over}}$ and $\overline{k_{under}}$ were then used to obtain the desired statistics with the formulas in Table 2 (derived in the Appendix).

The distributional characteristics of the data sets used to compute the semi-empiric parameters $\overline{GSD}$, $\overline{z_{Max}}$, $\overline{k_{under}}$, and $\overline{k_{over}}$ were examined to decide the best measure of their central tendency. Overall, data used for estimation of these semi-empiric statistics was not normally distributed; hence the *AM* was never selected. When we confirmed that the data followed a log-normal distribution, the *GM* was used as the best measure of the central tendency. However, when the shape of the distribution was not clearly right-skewed, we chose the median value as it is considered the most appropriate metric for general skewed distributions[27]. Finally, we estimated mid-point values for k_{over} and k_{under} using (eq. 4a) and (eq. 4b). The median value was selected as the best estimate of the central tendency for these correction factors, considering the assumptions that $k_{over}>1$ and $k_{under}<1$.

Confidence-weighting of pooled estimates

The lack of information on sample size and/or variance for many OEMD measurements ruled out inverse variance and other traditional measurement quality weighting procedures[28]. Therefore, a methodology was developed to weight our pooled measurements based on their quality and relevance for epidemiological studies, in particular for INTEROCC. The weighting approach was based on the use of expert confidence ratings as weights. These ratings had been initially used to include/exclude measurements from the OEMD[19]. INTEROCC experts, with experience in occupational EMF measurements, used a semi-quantitative approach to derive an average rating for each set of measurements extracted from a study. Using a confidence evaluation form published with the OEMD paper[19], each EMF expert first assigned a rating between 0 and 3 (0-1: low confidence; ≥1-2: moderate confidence; ≥2-3: high confidence) to eight specific factors of interest:

sampling strategy, sample size, type of statistic reported, duty factor, dosimetry type, anatomical location, nature of exposure scenario, and overall quality and reliability. Each set of measurements was rated by at least two experts and an average rating was assigned. We now used these ratings to adjust the pooled estimates to our confidence in the quality and relevance of the measurements.

Data pooling and calculation of confidence-weighted statistics

Finally, the EMF exposure statistics (AM_i & GM_i), for each OEMD record i, were pooled to obtain mean exposure statistics by EMF source, frequency band and dosimetry type, using the expert ratings as confidence weights (C_i). Thus, confidence-weighted means (${}_{cw}AM$ and ${}_{cw}GM$) and standard deviations (${}_{cw}SD$ and ${}_{cw}GSD$) were calculated for each electric or magnetic field with these formulas derived in the Appendix:

$$ {}_{cw}AM = \sum_{i=1}^{N} C_i N_i AM_i \Big/ \sum_i C_i N_i \tag{5} $$

$$ \ln {}_{cw}GM = \sum_{i=1}^{N} C_i N_i \ln GM_i \Big/ \sum_i C_i N_i \tag{6} $$

$$ {}_{cw}SD^2 = \frac{\sum_i C_i \left[\left(N_i - 1 \right) SD_i^2 + N_i \left(AM_i^2 - {}_{cw}AM^2 \right) \right]}{\sum_i C_i N_i - \left(\sum_i C_i^2 N_i \Big/ \sum_i C_i N_i \right)} \tag{7} $$

$$\ln^2{}_{cw}GSD = \frac{\sum_i C_i\left[\left(N_i - 1\right)\ln^2 GSD_i + N_i\left(\ln^2 GM_i - \ln^2{}_{cw}GM\right)\right]}{\sum_i C_i N_i - \left(\sum_i C_i^2 N_i \middle/ \sum_i C_i N_i\right)} \tag{8}$$

where N_i is the number of individual measurements *i* used to calculate the pooled summary statistics for each record *i* in the OEMD. When N_i was not available, the median N = 10 from the OEMD records was used. Equations 7 and 8 were derived from the general formula for the unbiased weighted sample variance with non-random (*a.k.a.,* reliability) weights[29], and become the classic formulas for the unweighted *SD* and *GSD* when $C_i = 1$.

Since measurement data pooling was performed by dosimetry type, pooled exposure estimates obtained from spot measurements comprise several distances while those obtained from personal or operator position involve several anatomical locations (e.g. head, chest). Due to the different availability of measurements, some sources in the SEM may have estimates for just one dosimetry type while others may have estimates for two or more. Maximum values, by source, frequency and dosimetry, were also included in the SEM, as well as information on the exact number of measurements pooled for each estimate.

To compare the values between pooled estimates for different dosimetries, we analyzed the overall difference between estimates for the same source by comparing different possible combinations (i.e. operator position versus spot; personal versus operator position and personal versus spot). For this analysis, we used the intraclass correlation coefficient (ICC) which, similarly to a one-way ANOVA, allows comparing continuous values between groups[30].

Quality control

To check the quality of the estimation process and ensure the assumptions in our semi-empiric methods were appropriate for OEMD data, we performed tests based on fundamental statistical characteristics of log-normal distributions (such as $Min<GM<AM<Max$) as well as more specific checks based on EMF's physical properties[19]. Manual calculations were also performed, comparing the results with those from the programmed algorithms. Errors identified were corrected, ensuring that both statistical characteristics and physical laws were not breached.

Analysis of variance (ANOVA)

To test the ability of the SEM to assign different exposures to subjects in an epidemiological study, we performed a one-way ANOVA with EMF source as the independent variable and the (reported or estimated) AM_i from OEMD as the response variable. Because of the large number of sources in the matrix and the diversity of frequencies and EMF magnitudes, as an example, we compared the values for mean electric fields for RF sources with three or more measurements at the operator position. Since ANOVA requires normal residuals and equal variances, data were log-transformed for this analysis. Furthermore, after confirming heterocedasticity (unequal variances between groups) using Levene´s test and assuming log-normality, we also used the non-parametric Welch´s test with untransformed data.

Validation

To test the validity of our methods to estimate summary statistics from the limited data in OEMD, Monte Carlo simulations were performed using the formulas in Table 1 on 10 000 random samples from a log-normal distribution with parameters similar to those found with EMF measurements (i.e. GM=20 and GSD=2.5). To make a realistic simulation, the sample size *N* for each simulation was drawn randomly from the values in the OEMD and the semi-empiric parameters were derived from the simulated data, using the methods described above for obtaining $\overline{z_{Max}}$ and $\overline{GSD}$. For each simulation, the relative errors in the summary statistic estimates for all methods were calculated relative to the sample statistics (*GM*, *AM*, *GSD*, *SD*) calculated from the *N* random draws:

$$\text{Relative error }\left(\text{RE}\right) = 100\% \frac{\text{Statistic estimate - Sample statistic}}{\text{Sample statistic}} \tag{9}$$

The mean of the RE over all simulations is, therefore, a measure of the bias, and its standard deviation equals the relative standard deviation (RSD), a measure of the precision. The overall uncertainty, which is considered an approximation to the accuracy[31,32] , can be estimated from these two values:

$$\text{Overall uncertainty } \equiv \left|\text{bias}\right| + 2 * RSD \approx \text{Accuracy} \tag{10}$$

Additionally, a split data set validation was performed for an RF source (dielectric heater), for which mean pooled estimates were obtained from 84 E-field measurements. The confidence-weighted arithmetic mean was computed using both a test subset (i.e. random 50% samples) and the entire data set, repeating these computations 1 000 times. To shed some light regarding possible changes over time for both exposure levels and measurements quality, we analyzed the available data for operator position measurements and confidence ratings – averaged by year – for two RF sources (aircraft radar, n=71, years=1974-1997; dielectric heater, n=84, years=1986-2004).

Finally, to test our hypothesis that the measurements used in the SEM follow a log-normal distribution, we used the Shapiro-Wilk test on log-transformed data from EMF sources with three or more records. All statistical analyses and graphics were performed using R, version 3.2.3[33].

RESULTS

Semi-empirical parameters $\overline{GSD}$, $\overline{z_{Max}}$, $\overline{k_{under}}$, and $\overline{k_{over}}$

Univariate statistics obtained for the parameters, $E_N[z_{Max}]$, *GSD*, k_{over} and k_{under}, are presented in Table 3. With $E_N[z_{Max}]$, its distribution over all N_i in OEMD was *a priori* unknown, so we chose its median as the central tendency ($\overline{z_{Max}}$ =1.54). *GSD* values tend to be log-normally distributed, so we chose its *GM* as the semi-empiric parameter ($\overline{GSD}$ =2.31). Following the logic with GSD´s central tendency that the models are linear in the parameters logarithms, the *GM* was selected as the central tendency measure for the corrections factors ($\overline{k_{over}}$ =1.47) and ($\overline{k_{under}}$ =0.48).

Exposure estimates in the SEM

The SEM contains *AM, GM* and maximum exposure estimates for 312 occupational sources of EMF exposure by frequency band, and estimates of their associated variability (*SD* and *GSD*). The maximum values for each source are the maxima of both the *Max* and *AM* values from the input OEMD records. Exposure estimates are provided for various types of dosimetry (i.e. personal, spot, operator position) as well as for literature reviews and expert judgments. In total, there are 401 combinations of EMF source, frequency band and dosimetry type. Table 4 summarizes the records used to obtain the different mean estimates. In total, over 3 000 measurements were compiled to create the SEM.

This table also outlines the different estimation methods used. Methods 2-5 were more frequently used, but methods 1, 6, 8 and 9 were used less often. More than 400 single measurements were used in the calculations; hence method 10 was also common. More than 50% of the estimates were obtained from 2 or more measurements, while the remaining values used only one measurement. As an example of the SEM results, Figure 1 shows the EMF sources with the minimum and maximum confidence-weighted geometric means (operator position) in the RF, IF and ELF frequency bands. Figure 2 shows the evolution of exposure levels and measurement quality for two RF sources over time. A considerable decrease of exposure levels and a slight increase of data quality are appreciable.

The confidence evaluation process

A total of 268 quantitative ratings were used as weights, since the same rating was assigned to two or more measurements if they shared the same characteristics. Of these, 135 (~50%) are above 2 (high confidence), 120 (~45%) are between 1 and 2 (moderate confidence) while only 13 ratings (~5%) are below 1 (low confidence). To illustrate the impact of the weighting process in the SEM calculations, Figure 3 shows the distribution of the E-field measurements used to calculate the mean (spot) estimate for the RF source “continuous shortwave diathermy”. These plots show weighted and unweighted regression lines over distance, highlighting the impact of the ratings on the weighted line (dashed). In our pooled summary statistics (eqs. 5-8), measurements rated as low confidence are similarly downplayed while moderate and high confidence values have a stronger influence on the final estimate.

ANOVA

In the ANOVA analysis to assess the ability of the SEM estimates to assign exposure variation for epidemiological analysis, the RF source explained almost 60% of the variability of the E-field and these differences were significant ($p<0.0001$). The Welch´s test ($p<0.0001$) also confirmed these results.

Validation

The simulations based on the estimation formulas in Table 1 yielded overall uncertainties (i.e. accuracy) for GM and AM estimates between 47-143% (Table 5). For variability statistics, GSD estimates were obtained with accuracies between 33-78% while SD estimates yielded extreme overall uncertainties. An additional simulation using different N values showed a clear pattern of better performance with larger sample sizes (data not shown). Furthermore, these simulations showed that some estimation methods have less overall uncertainty when $\overline{z_{Max}}$ is used instead of $E_N[z_{Max}]$ (see Table A-III in the Appendix). Hence, our SEM calculations used the z_{Max} parameter which gave the best accuracy in the simulations of each statistic / method combination in Table 5. The split data set validation yielded a median relative error of -18%.

The Shapiro-Wilk test confirmed the log-normal hypothesis (p-value > 0.05) in around 85% of the analysed sources. The ICC analysis showed moderate to substantial agreement for the compared dosimetries (i.e. ICC=0.80 for spot versus operator position, n=18; ICC=0.69 for personal versus operator position, n=9; ICC=0.53 for spot versus personal dosimetries, n=20).

DISCUSSION

This work allowed the construction of a SEM containing estimated exposure statistics for the most common occupational sources of EMF exposure, identified through the INTEROCC study questionnaire. This database represents a new approach for occupational exposure assessment, based on EMF sources independent of occupation. The SEM will be available on-line as a free-access tool at http://www.crealradiation.com/index.php/es/databases. Although the current version does not include all possible EMF sources, it can be updated with new or newly identified measurements and sources.

One advantage of the source-based approach is that personal determinants of exposure obtained from questionnaires should reduce Berkson errors, increasing the validity and reliability of both exposure and risk estimates[15]. However, the SEM mean exposures will still leave residual Berkson errors due to the combination of measurements from different studies and locations (i.e. distances or anatomical positions). Another advantage is the SEM´s ability to evaluate occupational exposures to RF and IF fields. Since no JEM yet exists for these higher frequencies, only a source-based approach can provide quantitative estimates of exposure for INTEROCC and other studies. The results of the ANOVA and the non-parametric test confirmed the existence of significant between-source variability, which allows the assignment of different exposures to study subjects, necessary for identifying exposure-response relationships in risk analysis. Previous efforts to reduce exposure misclassification included the development of task-exposure matrices for other agents[34–37]. However, earlier advocates of a source-based approach for EMF exposure assessment[38–41] recommended the use of combined estimates from a JEM together with information such as duration and location related to specific sources of exposure. To our knowledge, this is the first time that a full source-based approach, independent of the occupation, has been attempted.

The mean exposure (i.e. *AM* or *GM*) was selected as the central metric in the SEM because it best represents measurements taken in diverse settings. There has been considerable discussion whether the *AM* or *GM* from JEMs best reduces Berkson errors in an epidemiological analysis[42–45], and these same considerations apply to the SEM. Although the *GM* is the best estimate of the central tendency for log-normally distributed data, the *AM* has been considered the best summary measure for linear and convex dose-response relationships, while the *GM* would be a better metric when the proposed mechanism is log-linear (i.e. the response is proportional to the logarithm of the exposure/dose)[45–49]. The availability of both *AM* and *GM* in the SEM allows to select the more appropriate metric for the study hypothesis. The provision of within-source variability statistics (i.e. ${}_{cw}SD$ and ${}_{cw}GSD$) also allows to correct risk estimates for bias attributable to Berkson error as well as for uncertainty propagation analysis[18,50–52]. Moreover, although bias estimates were provided for only half of the methods, the use of this information as weights for the pooled statistics should be explored in the future.

Several methods were developed for estimating parameters based on scarce measurement data. Methods 1 and 2 require enough available data to derive *AM*, *GM*, *GSD*, and *SD* from exact relationships between the true statistics of a log-normal distribution[24]. Method 2, in particular, was based on an estimation formula,

$\widehat{GM} = \sqrt{Min * Max}$, which has recently been popularized by physicists for "guesstimation"[53,54] and variants have been used in exposure assessment efforts[3,4,7]. To extend this estimation technique to the other combinations of statistics, we introduced several semi-empirical methods to derive equations where the literature provided insufficient data for exact solutions. Although these semi-empiric estimates fill many of the gaps in the diverse data available, they add to the uncertainties of the exposure assessment, as shown by the simulations in Table 5. Moreover, the method we used to reliably estimate parameters from only maximum values, as proved by the relatively low bias obtained in the simulations, provides a novel approach which, to our knowledge, was lacking in the present literature. For data combinations not considered in Tables 1 and 2, which may also be found in the literature, we provided the assumptions and premise formulas needed to easily derive appropriate methods.

We provided evidence for the reliability of our methodology through both simulations and a split data-set validation. While the simulated accuracies are far greater than the 25% accuracy criterion established by NIOSH for occupational exposure measurements[31], most methods for *GM* had overall uncertainties of 53% or less, which we consider sufficient for retrospective epidemiology. Moreover, these accuracies are expected to improve if *GSD* and/or *SD* are extracted from the literature or larger sample sizes are used, as seen in our additional simulations and previous studies[55]. However, the impact of these larger exposure assessment errors on risk estimates should be investigated. For the methods in Table 2, a comprehensive approach for evaluating uncertainties was not found. Although some of the estimated values violated the assumptions k_{over}>1 and k_{under}<1, one of the semi-empirical estimated parameters ($\overline{k_{over}}$ =1.47) compared well with a calculated value (k_{over} =1.41) based on empirical monitoring data (i.e. measurements of the same location using two different ELF-MF meters at a car factory in the Netherlands). However, further validations would be advisable for these ccorrection factors as well as for the equations in Tables 1 and 2.

The influence of measurement quality on exposure and risk estimates requires a rigorous evaluation, including transparency in the way data are weighted for their actual or relative value[28,56]. Some authors[5,6,28] proposed the use of sample size or inverse variance to obtain quality-weighted exposure estimates. However, the frequent lack of this information for measurements in the EMF literature makes the use of such approaches unfeasible. We used expert confidence ratings to adjust our estimates to the quality and relevance of the pooled measurements, overcoming this difficulty. The scoring system we selected is in agreement with a recent proposal for the evaluation of exposure data quality[28], where a method to classify measurements in four quality groups (i.e. good, moderate, poor and unacceptable) is proposed. Although we did not distinguish between poor and unacceptable measurements, those rated as low confidence (0-1) were generally excluded from the pooling. However, some low confidence measurements, for which no better data were available, were included in the SEM. Based on this confidence classification, sensitivity analysis may be conducted (e.g. excluding lower quality data). This method also allows accounting for sampling characteristics, while other weighting approaches, such as inverse variance, only take into account the statistical uncertainty and do not consider other potentially important factors (e.g. quality of the task description and the sampling devices or focus on high exposures) which can be easily identified in the literature and may determine the quality and relevance of a measurement[28]. Thus, similarly to meta-analysis in epidemiology[57], measurements with higher confidence have a larger contribution to the weighted mean. Finally, this approach allowed the raters to use a simple additive method to assign scores, which has been shown to be a good predictor of overall methodological quality[58,59].

One possible weakness of the SEM was our need to include the less accurate spot and operator position dosimetries in order to provide exposure data for some of the reported sources. However, the results of the ICC showed that the overall differences between the three dosimetry types are small. Estimates obtained from operator position or spot measurements may, therefore, be reliably used as surrogates of personal exposure when this is not available. Moreover, confidence-weighted estimates were adjusted to head exposure through the confidence weighting process. Measurements made at head location obtained higher ratings and were upgraded in the pooling. To allow use of the SEM in studies on other locations (e.g. chest, gonads) – where different weighting approaches may be applied – the unweighted estimates were also provided. Since the confidence evaluations for all eight factors are stored in the SEM database, future studies may reduce the weight given to head measurements while retaining the other seven factors affecting measurement quality.

Another weakness is the lack of use of anatomical location and distance information collected in the OEMD for spot and operator position measurements. SEM values refer, therefore, to average levels over different exposure scenarios, which provide the within-source variability inherent within each mean estimate. Pooled estimates represent different situations of exposure depending on the dosimetry type. Estimates for personal and operator position comprise measurements at different anatomical locations (e.g. head, chest, or waist) while spot estimates include exposures at different distances (e.g. 30-100 cm for most ELF sources). However, as shown in Figure 2, the availability of this information in OEMD may allow future modelling of exposures at specific distances and locations, useful in studies interested in other body parts.

The analysis of the available measurement data for different years showed signs of a slight data quality increase over time, which is reasonable considering the improvements in industrial hygiene[60]. Exposure levels, on the contrary, showed a clear decrease pattern, which is in line with the trends shown by other technologies such as mobile phones[61]. However, since level changes are limited to one order of magnitude and OEMD data for the same source seldom span several years, we do not expect that these changes will have a strong effect on the SEM estimates.

The SEM can be used to assess EMF exposures for other occupational and residential epidemiologic studies that have collected individual information on the use of EMF sources. Such studies require questionnaires that elicit individual information about the type of EMF sources used/exposed, as well as about conditions of use (e.g. distance to the source, automation) to adjust the SEM estimates to the specific tasks and work characteristics of the individual. If the time-weighted average or cumulative exposures are desired, the questionnaire also needs to obtain information on the frequency and duration of use/exposure. In INTEROCC, industry was considered through the classification of all EMF sources into twelve occupational sections[19]. Therefore, the variability due to industrial differences is embedded within the type of source itself, which together with the aforementioned information on other exposure determinants allows a detailed estimation of a subject´s level of exposure. While the means in the SEM are most useful in chronic disease studies, the EMF maxima can be applied to acute effects, such as electromagnetic interference with pacemakers and other medical devices[62].

In conclusion, the methodology described allowed the construction of the first SEM for EMF exposure assessment, based on measurements identified in the literature, and supplemented with expert judgment estimates for sources without available measurements. These methods made use of measurement data which more conventional methods would have discarded. Although more analyses are needed on their uncertainty and validity, they may also be useful for other physical and chemical agents for which available measurement data are sparse and traditional methods are insufficient.

The SEM will be used to estimate cumulative RF and ELF exposures of the INTEROCC subjects, through algorithms which combine SEM means with individual data on exposure determinants collected by interviews. This more individualized exposure assessment will potentially increase within-job variability among subjects and reduce uncertainty due to misclassification and Berkson errors. We expect that this approach will strengthen our ability to evaluate potential health effects from EMF exposures.

ACKOWLEDGEMENTS

The authors would like to thank Dave Conover (deceased), Ed Mantiply and Leeka Kheifets (USA); Dave McLean (New Zealand); Hans Kromhout (the Netherlands); Paolo Vecchia (Italy); Louis Nadon (Canada); Wout Joseph (Belgium); Martie van Tongeren, Simon Mann, Myron Maslanyj, Cristian Goiceanu and Carolina Calderon (UK), Peter Gajšek (Slovenia), and Tommi Alanko, Maila Hietanen and Maria Tiikkaja (Finland), for providing and/or assessing measurements. Jérôme Lavoué (Canada) and Stanley Shulman (US) contributed to the development of the SEM methodology. The authors would also like to thank Prof. Pere Puig (Autonomous University of Barcelona) for his input on the history of estimation.

The Appendix is available as supplementary material at the Journal of Exposure Science and Environmental Epidemiology´s website.

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TABLES & FIGURES

Table 1. Formulas for estimating *AM, GM, SD* and *GSD* from the OEMD data, not including values outside the dynamic range (ODR). Notation: Hats denote estimates; bars denote semi-empiric parameters; other variables are input values.

Method #	**OEMD data**	**Estimated statistic**	**Formula**	**Assumptions**[d]
1	[a]*N, Min, Max* & *AM*	$\widehat{AM} =$	AM	—
		$\widehat{GSD} =$	$\left(\sqrt{Max/Min}\right)^{1/E_N[z_{Max}]}$	A or B[a]
		$\widehat{GM} =$	$\mathrm{AM} \Big/ \sqrt{\widehat{GSD}^{\ln \widehat{GSD}}}$	—
		$\widehat{SD} =$	$\frac{AM}{\widehat{GM}}\sqrt{AM^2 - \widehat{GM}^2}$	—
2	*N, Min* & *Max*	$\widehat{GM} =$	$\sqrt{Min * Max}$	—
		$\widehat{GSD} =$	$\left(\sqrt{Max/Min}\right)^{1/\overline{z_{Max}}}$	B
		$\widehat{AM} =$	$\widehat{GM}\sqrt{\widehat{GSD}^{\widehat{GSD}}}$	—
		$\widehat{SD} =$	$\frac{\widehat{AM}}{\widehat{GM}}\sqrt{\widehat{AM}^2 - \widehat{GM}^2}$	—
3	[a]*N* & [b]*Max*	$\widehat{GM} =$	$Max \Big/ \overline{GSD}^{E_N[z_{Max}]}$	A
		$\widehat{AM} =$	$Max\sqrt{Q^{-2E_N[z_{Max}]}}$, where $Q = \overline{GSD}^{\ln \overline{GSD}}$	A or B[a], C
		[c]$\widehat{GSD} =$	$\overline{GSD}$	C
		$\widehat{SD} =$	$\frac{\widehat{AM}}{\widehat{GM}}\sqrt{\widehat{AM}^2 - \widehat{GM}^2}$	—
4	*AM*	$\widehat{AM} =$	AM	—
		$\widehat{GM} =$	$AM \big/ \sqrt{Q}$	C
		$\widehat{GSD} =$	$\overline{GSD}$	C
		$\widehat{SD} =$	$\frac{AM}{\widehat{GM}}\sqrt{AM^2 - \widehat{GM}^2}$	—
5	*GM*	$\widehat{GM} =$	GM	—
		$\widehat{AM} =$	$GM\sqrt{Q}$	C
		$\widehat{GSD} =$	$\overline{GSD}$	C
		$\widehat{SD} =$	$\frac{\widehat{AM}}{GM}\sqrt{\widehat{AM}^2 - GM^2}$	—

[a]Where *N* is not available, $E_N[z_{Max}]$ is replaced with $\overline{z_{Max}}$ which equals the median $E_N[z_{Max}]$ from all available *N* values (except for method #2, see main text). [b]Formulas when *Min* is the only input data are omitted because this case does not occur in the OEMD. [c]The semi-empiric parameter $\overline{GSD}$ is calculated from OEMD records with data for methods #1 & #2. [d]In addition to the log-normality assumption and the symmetric quantile approximation (eq. 2), additional assumptions were needed to derive some formulas: A) Expected normal order statistic approximation: $z_{Max} = E_N[z_{Max}]$; B) Semi-empiric value for z_{Max}; C) Semi-empiric value for GSD.

Table 2. Formulas for calculating *AM, GM, SD,* and *GSD* from OEMD data, including values outside the dynamic range (ODR). Notation: Hats denote estimates; bars denote semi-empiric parameters; other symbols are input values

Method #	OEMD data	Estimated statistic	Formula	Assumptions[d]
6	[b]*N, Min, ODRMa*x & *AM*	[a]$\widehat{k_{over}}$ =	$\frac{AM^2}{Min * ODRMax * \sqrt{Q}}$	C & D
		$\widehat{AM}$ =	AM	—
		$\widehat{GSD}$ =	$\left(ODRMax * \overline{k_{over}} / Min\right)^{1/2E_N[z_{Max}]}$	A or B[b], & D
		$\widehat{GM}$ =	$\sqrt{Min * \overline{k_{over}} * ODRMax}$	D
		$\widehat{SD}$	$\frac{AM}{\widehat{GM}}\sqrt{AM^2 - \widehat{GM}^2}$	—
7	[b]*N, ODRMin, Ma*x & *AM*	[a]$\widehat{k_{under}}$ =	$\frac{AM^2}{ODRMin * Max * \sqrt{Q}}$	C & E
		$\widehat{AM}$ =	AM	—
		$\widehat{GSD}$ =	$\left(Max / ODRMin * \overline{k_{under}}\right)^{1/2E_N[z_{Max}]}$	A or B[b], & E
		$\widehat{GM}$ =	$\sqrt{ODRMin * \overline{k_{under}} * Max}$	E
		$\widehat{SD}$ =	$\frac{AM}{\widehat{GM}}\sqrt{AM^2 - \widehat{GM}^2}$	—
8	[b]*N, Min & ODRMax*	$\widehat{GM}$ =	$\sqrt{Min * \overline{k_{over}} * ODRMax}$	D
		$\widehat{GSD}$ =	$\left(ODRMax * \overline{k_{over}} / Min\right)^{1/2E_N[z_{Max}]}$	A or B[b], & D
		$\widehat{AM}$ =	$\widehat{GM}\sqrt{\widehat{GSD}^{\widehat{GSD}}}$	—
		$\widehat{SD}$ =	$\frac{\widehat{AM}}{\widehat{GM}}\sqrt{\widehat{AM}^2 - \widehat{GM}^2}$	—
9	[b]*N,* ODR*Min & Max*	$\widehat{GM}$ =	$\sqrt{Max * \overline{k_{over}} * ODRMin}$	E
		$\widehat{GSD}$ =	$\left(Max / ODRMin * \overline{k_{under}}\right)^{1/2E_N[z_{Max}]}$	A or B[b], & E
		$\widehat{AM}$ =	$\widehat{GM}\sqrt{\widehat{GSD}^{\widehat{GSD}}}$	—
		$\widehat{SD}$ =	$\frac{\widehat{AM}}{\widehat{GM}}\sqrt{\widehat{AM}^2 - \widehat{GM}^2}$	—

[a]OEMD records with the data in methods #6 and #7 are used to calculate the semi-empiric parameters $\overline{k_{over}}$ and $\overline{k_{under}}$.

[b]Where *N* is not available, $E_N\,[z_{Max}]$ is replaced with $\overline{z_{Max}}$ which equals the median of $E_N[z_{Max}]$ from all available *N* values in OEMD. [d]In addition to the log-normality assumption and the symmetric quantile approximation (eq. 2), additional assumptions were used to derive some formulas: assumptions A-C from Table 1, D) semi-empiric value for k_{over}; E) semi-empiric value for k_{under}.

Table 3. Descriptive statistics for the estimated parameters calculated from sub-sets of the OEMD data. The statistics selected as a central tendency for use as semi-empiric parameters in Tables 1 and 2 are marked **in bold.**

Statistics	$E_N[z_{\mathrm{Max}}]$	*GSD*	[a]k_{over}	[b]k_{under}	[c]N
# records	372	100	7	22	372
Min	0.56	1.1	0.09	0.01	2
Max	3.26	6.4	18.44	44.54	1075
AM	1.45	2.59	5.69	5.81	19
Median	**1.54**	2.09	0.26	0.58	**10**
GM	1.33	**2.31**	**1.47**	**0.48**	9
SD	0.56	1.3	8.00	13.70	59
CV%	39%	67%	141%	236%	3%

[a]k_{over} values less than 1 were not included in the calculations.
[b]k_{under} values greater than 1 were not included in the calculations.
[c]N=1 records were not considered in this table nor in the simulations.

Table 4. Description of estimation methods and measurements used in the SEM

Estimation method # (data available)	Number of OEMD measurements					
	E-field	H-field	B-field	PD	Total	%
1 (*AM*, *Min* & *Max*)	13	2	156	4	175	8
2 (*Min* & *Max*)	226	133	115	40	514	23
3 (*Max*)	269	163	134	30	596	27
4 (*AM*)	71	34	317	17	439	20
5 (*GM*)	12	18	19	0	49	2
6 (*AM*, [a]ODR*Max* & *Min*)	0	0	1	0	1	0.1
8[b] (*Min* & ODR*Max*)	4	1	0	2	7	0.3
9 (*Max* & ODR*Min*)	0	0	1	0	1	0.1
10[c] (single measurement)	218	35	95	88	436	20
# measurements per estimate	Number of SEM estimates					
1 measurement	98	152	142	--	392	49
2 measurements	23	51	31	--	105	13
3-5 measurements	31	76	59	--	166	21
6-10 measurements	23	35	31	--	89	11
> 10 measurements	14	21	11	--	46	6

[a]ODR: Outside Dynamic Range. [b]Estimation method 7 (*AM*, ODR*Min* & *Max*) was not used since the OEMD did not have any cases with these values. [c]OEMD records with N=1 (i.e. single measurements) were considered as $AM = GM$, hence method 10 is not considered for Tables 1 & 2.

Table 5. Uncertainties of the methods in Table 1 for estimating unknown summary statistics. The uncertainty measures are calculated with Monte Carlo methods with 10 000 simulations of a random sample from a log-normal distribution with *GM* = 20, *GSD* = 2.5, and sample size [a]*N* randomly drawn from those in OEMD.

Estimated statistic	**Measures of the relative error (RE)**	Estimation method[a] (*statistics with values from simulated sample*[b])				
		1 (*AM, Min & Max*)	**2 (*Min & Max*)**	**3 (*Max*)**	**4 (*AM*)**	**5 (*GM*)**
$\widehat{GM}$	Mean RE (bias)	-12%	3%	14%	-5%	
	SD of RE (precision)	17%	25%	64%	21%	
	Accuracy	47%	53%	143%	47%	
$\widehat{AM}$	Bias		21%	16%		9%
	Precision		52%	36%		20%
	Accuracy		125%	88%		50%
[c]$\widehat{GSD}$	Bias	6%	6%	9%	9%	9%
	Precision	13%	13%	35%	35%	35%
	Accuracy	33%	33%	78%	78%	78%
$\widehat{SD}$	Bias	37%	85%	72%	113%	170%
	Precision	74%	254%	411%	1 101%	1 651%
	Accuracy	185%	593%	894%	2 316%	3 472%

[a]Estimation methods #1, 3, 4 & 5 use $E_N[z_{Max}]$ while method #2 uses $\overline{z_{Max}}$ (i.e. median of $E_N[z_{Max}]$). [b]The median of the *N* values in OEMD = 10. [c]Methods #3-5 for $\widehat{GSD}$ have the same results since they all use $\overline{GSD}$.

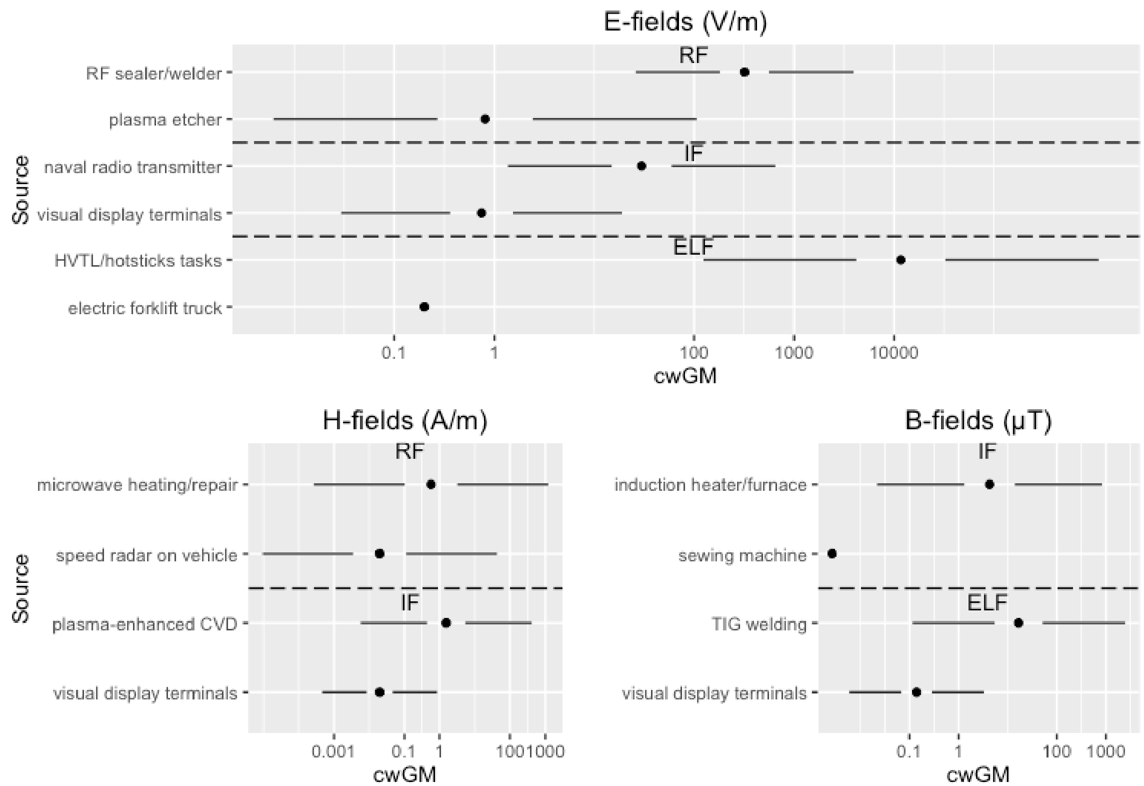

Figure 1. Quartile plots (25th and 75th percentiles) for EMF sources in the SEM with the highest and lowest cwGM for E-, H- and B-fields for operator position by frequency band. Estimates without whiskers (i.e., "electric forklift truck" and "sewing machine") were obtained from only one measurement. CVD, chemical vapor deposition; EMF, electromagnetic field; HVTL: high-voltage transmission lines; SEM, source-exposure matrix; TIG, tungsten inert gas.

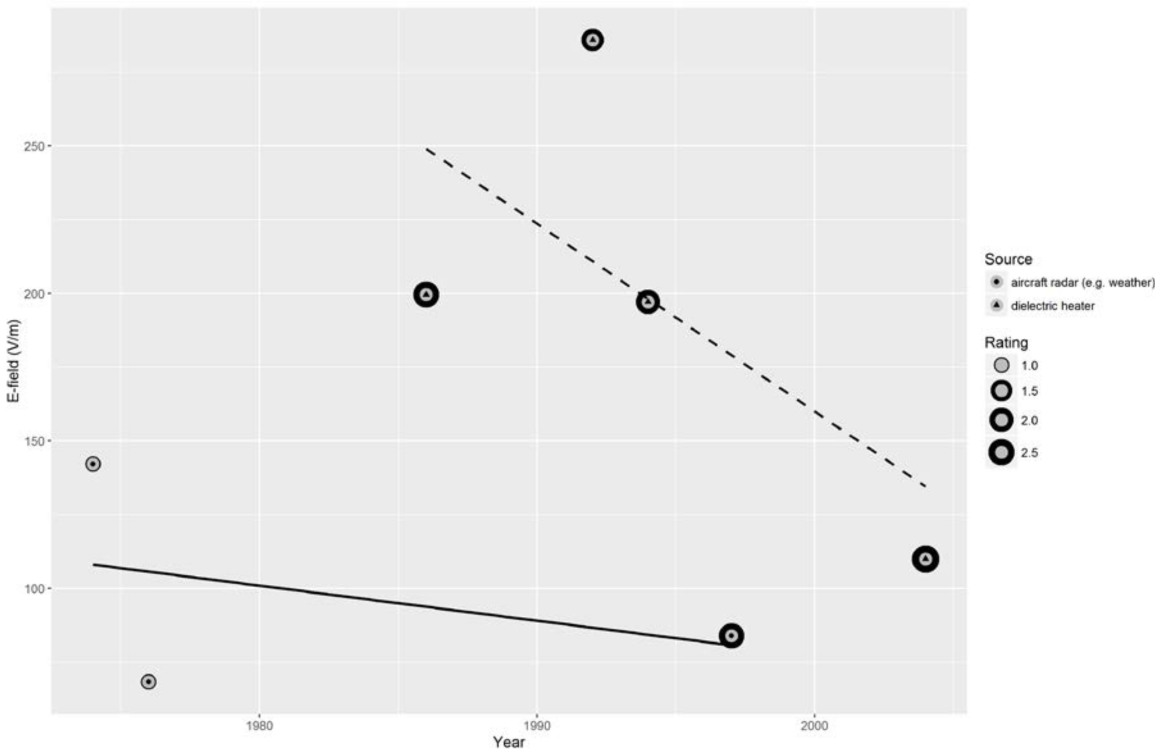

Figure 2. Operator position E-field measurements for two RF sources (i.e., aircraft radar and dielectric heater) collected from documents covering the time span 1974–2004. Data points and corresponding confidence ratings (i.e., the size of the point) were obtained by averaging the available data by year. The lines represent modeled linear regressions based on the averaged data. RF, radiofrequency

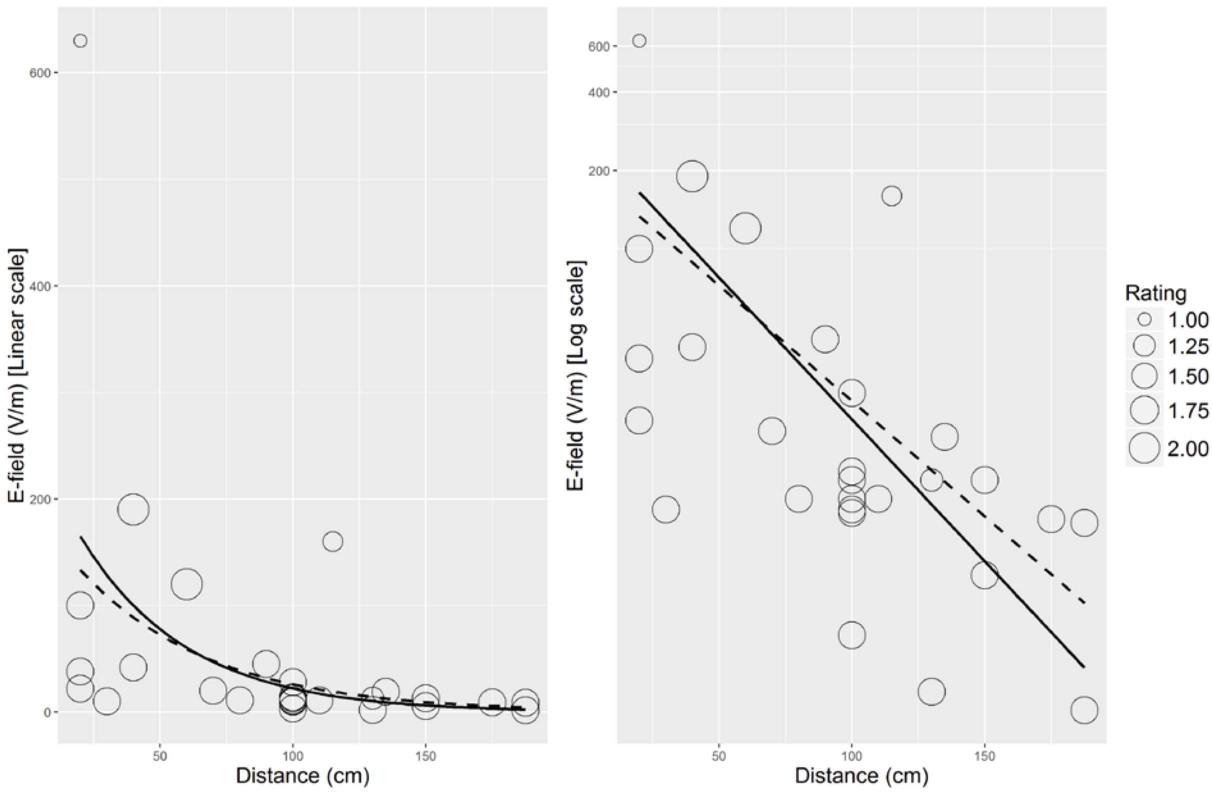

Figure 3. E-field measurements versus distance for OEMD data used to estimate the confidence-weighted mean exposure for the source “continuous shortwave diathermy” in the SEM. The bubbles represent data points with size proportional to the assigned rating level. The lines represent modeled exponential regression lines (dashed line, weighted) with the y axis in the linear (left graph) and logarithmic (right graph) scales. No ratings were assigned to these measurements below 1 or above 2. Thus, the “Rating” legend only includes a scale of sizes between these levels. OEMD, occupational exposure measurement database; SEM, source-exposure matrix.

Appendix:

Statistical Methods Developed for the INTEROCC Study's Assessment of EMF Exposures

by J.D. Bowman and J. Vila

for the manuscript

"Development of a source-exposure matrix for occupational exposure assessment of electromagnetic fields in the INTEROCC Study" by Vila, Bowman et al.

Published in the *J Expo Sci Environ Epidemiol.*

Summary

We here derive the formulas for calculating the confidence-weighted arithmetic means (*AM*), geometric means (*GM*) and their corresponding standard deviations (A*D* and *GSD*) from EMF data obtained from the Occupational Exposure Measurement Database (OEMD). In part A of this appendix, we derive the formulas in Tables 1 and 2 for estimating summary statistics which are not in OEMD. Part B contains derivations for the confidence weighted means and standard deviations from OEMD's summary statistics

A. *Semi-empirical methods for estimating summary statistics for the SEM*

The problem is to estimate these statistics from sparse information, typically the minimum (*Min*) and maximum (*Max*) but also the number of measurements (*N*), arithmetic or geometric mean, and outside-dynamic-range values (*ODRMin* or *ODRMax*). Our solution is to derive the summary statistics from the assumption that the exposure data are distributed log-normally, and any unknown variable (such as the *GSD*) needed to complete the derivation is replaced with its central tendency calculated from an appropriate data set – a semi-empirical approach.

This approach is an extension of the expert judgment method developed by Bowman, Sivaganesan, Shulman and Cardis [2013], which starts with the log-normal relationships for the standard normal quantiles, *z*, corresponding to *Min* and *Max*:

$$\ln Min = \ln GM + z_{\mathrm{Min}} \ln GSD \qquad \text{(A1a)}$$

$$\ln Max = \ln GM + z_{Max} \ln GSD \qquad \text{(A1b)}$$

By adding and subtracting these two equations, Bowman et al. [2013] derived formulas for estimating *GM* and *GSD* as functions of *Min* and *Max*:

$$ln\widehat{GM} = \ln GME - \frac{\alpha}{2}\left(\ln Max - \ln Min\right) \qquad \text{(A2a)}$$

$$ln\widehat{GSD} = \frac{1}{2\zeta}\left(\ln Max - \ln Min\right) \qquad \text{(A2b)}$$

where the hat designates estimates and the symbols α, ζ, and *GME* are defined as:

$$\alpha \equiv \frac{z_{\text{Max}} + z_{\text{Min}}}{z_{\text{Max}} - z_{\text{Min}}} \qquad \zeta \equiv \tfrac{1}{2}\left(z_{\text{Max}} - z_{\text{Min}}\right) \tag{A3}$$

$$GME = \text{ geometric mean of the extremes} \equiv \sqrt{Max * Min} \tag{A4}$$

The parameter α is an asymmetry parameter that measures how far z_{Min} and z_{Max} deviate from being symmetric about zero (*i.e.* $z_{Min} = - z_{Max}$). ζ is the average distance of z_{Min} and z_{Max} from the mean of the log-transformed data, and therefore serves as the "effective quantile" in the estimation formula for the *GSD* (eq. A2b). *GME*, the geometric mean of the extreme values (*Min* and *Max*), has a long history, which we traced back from Enrico Fermi through Voltaire, Sir Isaac Newton and Euclid to the Pythagorean mathematician Archytas in the fifth century BCE [Bowman and Vila, unpublished].

In expert judgment studies, values for *Min* and *Max* are elicited from an expert panel, which provides values for two of the four variables on the right hand side of the two equations for *GM* and *GSD* (eqs. A2). The two remaining unknown variables, α and ζ, are the semi-empirical parameters, whose central tendencies $\overline{\alpha}$ and $\overline{\zeta}$ (means or medians as best fits the calibration data) are calculated from the expert judgment results with a calibration data set whose *GM* and *GSD* are known. After determining $\overline{\alpha}$ and $\overline{\zeta}$, estimated summary statistics, $\widehat{GM}$ and $\widehat{GSD}$, can then be calculated for exposures beyond the calibration set with eqs. A1, using only their *Min* and *Max*. Next, the *AM* and *SD* are derived from the exact relationships between the statistics of a log-normal distribution [Aitchison and Brown, 1957]:

$$\ln AM = \ln GM + \tfrac{1}{2}\ln^2 GSD \tag{A5}$$

$$SD = \frac{AM}{GM}\sqrt{AM^2 - GM^2} \tag{A6}$$

Formulas for all the statistics in the expert judgment method are in the first row of Table A-I. Note that the formulas in Table A-I are the anti-logs of eqs. A2 and A6, which results in more compact equations with greater computational efficiency.

Summary statistics from OEMD data

A similar approach is used to estimate summary statistics with data from OEMD, although the formalism is made more complicated by the many combinations of *Min, Max, AM, GM, N, ODRMin,* and/or *ODRMax* whose values were extracted into OEMD from different publications. In order to structure a semi-empirical derivation of formulas for all the summary statistics, we start with a theorem from algebra that a system of simultaneous polynomial equations has solutions if the number of equations equals the number of unknown variables.

With the formalism outlined above, there are 2 linear equations (eqs. A2a and A2b). (Note that the log-transformed statistics like ln *GM* and ln *Min* are treated as the variables in order to make these equations linear). If eq. A4 is substituted into eq. A2a, these two have a total of 6 linear variables (ln *GM*, ln *GSD*, ln *Max*, ln *Min*, α and ζ). Since values for *Max* and *Min* are provided by the expert panel, only four of the variables are unknown, but this is greater than the number of equations, leaving their solution underdetermined. In order to evaluate the formal solutions for the unknowns, $\widehat{lnGM}$ and $\widehat{lnGSD}$ in eqs. A2, the expert judgment method therefore provided values for the 2 semi-empiric variables α and ζ. This reasoning can be expressed numerically as:

2 equations = 2 unknowns = 6 total variables – 2 variables with values – 2 semi-empiric variables (A7)

An algebraic form of eq. A7 can be re-arranged into a general expression for the number of semi-empiric variables needed to solve a system of simultaneous equations:

$$s = t - m - v \tag{A8}$$

where s = number of semi-empiric variables, t = total number of variables, m = number of equations, and v = number of variables with values.

To illustrate the application of this semi-empirical method to OEMD data, consider a record with values for *Min* and *Max*, so there are v=2 variables with values (method #2 in Table A-I). To obtain estimates for *GM* and *GSD*, we use eqs. A2a and A2b, creating a system of m=2 simultaneous equations with t = 6 variables. According to eq. A8, values are needed for s = 2 semi-empiric variables in order to solve these two equations for the unknown summary statistics.

The first semi-empiric variable is provided by assuming $z_{Min} = -z_{Max}$, so that $\alpha = 0$ (eq. A-3). We call this "the symmetric quantile" assumption because the minimum and maximum quantiles are symmetric about zero (the mean quantile), and the corresponding percentiles also have the symmetry $P_{Min} = 1-P_{Max}$, (e.g. the 5th and 95th percentiles). The symmetric quantile assumption makes eq. A2a into $\widehat{lnGM} = \ln GME$, whose anti-log is the estimation formula in Table A-I.

From the definitions of α and ζ (eqs. A3), this assumption also implies that $z_{Max} = -z_{Min} = \zeta$, so eq. A2b becomes ln $\widehat{GSD}$ = (ln *Max* – ln *Min*)/2z_{Max}. A solution for $\widehat{GSD}$ therefore requires the second semi-empiric parameter $\overline{z_{Max}}$, where the bar represents the central tendency of z_{Max} calculated exactly from the formula in Table A-I from OEMD records with v=3. With semi-empiric estimates for $\widehat{GM}$ and $\widehat{GSD}$, *AM* and *SD* can now be estimated with the relationships A5 and A6 between exact values for the summary statistics of a log-normal distribution, as shown for method #2 in Table A-I.

Note that the formulas for *SD* in Table A-I only require values for *AM* and *GM*, which are either input values or have already been estimated by the other formulas in Table A-I. Since the same situation applies to all other combinations of input data in Tables A-I and A-II, slight variations of eq. A6 are used to estimate *SD* throughout the SEM calculations.

With 2 or less variables with values in an OEMD record, semi-empiric values are needed in addition to the $\alpha = 0$ assumption to obtain solutions for the missing summary statistics. As shown in Table A-I, $v = 2$ values for *Max* and *Min* requires a central tendency for $\overline{z_{\text{Max}}}$ in order to estimate the summary statistics, while a record with a value for only *Max* ($v = 1$) requires an additional central tendency for $\overline{GSD}$. These central tendencies are calculated from a sub-set of OEMD records with values for enough variables for the simultaneous equations to have exact solutions (i.e. $s \le 0$). Whether the median, AM or GM is the best central tendency for these semi-empiric parameters is addressed in the main paper.

Summary statistics from OEMD data that include N

In addition to the summary statistics examined above, some OEMD records also contained the number of measurements *N* used to calculate the statistics. To employ the reported *N* values in our summary statistic estimates, z_{Max} and z_{Min} are equated to their expected values for a sample of *N* quantiles *z* from the standard normal distribution (Zwillinger and Kokoska 2000). When the *N* expected values $\text{E}_N[z]$ are ranked according to their values, these "expected normal order statistics" [also called "rankits" by Ipsen and Jerne (1944)] are widely used in normal probability plots (Snedecor and Cochran, 1989).

In the SEM calculations, the expected normal order statistics for the extreme quantiles, $E_N[z_{\text{Max}}]$ and $E_N[z_{\text{Min}}]$, are calculated by a numeric algorithm (Royston, 1982) and assumed to equal the actual minimum and maximum quantiles for OEMD records that have values for the sample size *N*:

$$z_{\text{Min}} = E_N[z_{\text{Min}}] \quad \text{(A9a)}$$

$$z_{\text{Max}} = E_N[z_{\text{Max}}] \quad \text{(A9b)}$$

In addition, the extremes of the expected normal order statistics for a given *N* are symmetric (Zwillinger and Kokoska 2000):

$$E_N[z_{\text{Min}}] = -\,E_N[z_{\text{Max}}] \quad \text{(A10)}$$

In other words, they fulfil the symmetric quantile ($\alpha = 0$) assumption.

Using these results in the summary statistics calculations, there are now $n = 6$ simultaneous equations (eqs. A1a, A1b, A5, A9a, A9b and A10) with 2 additional variables with values ($E_N[z_{\text{Min}}]$ and $E_N[z_{\text{Max}}]$), giving a total of $t = 9$ variables. When OEMD has *Min*, *Max* and *AM* in addition to *N*, the number of variables with values is now $v = 5$, so eq. A8 now gives $s = -1$. This negative result means there are more simultaneous equations than unknown variables, so this over-determined system of equations has more than one solution for both *AM* and *GM* in Table A-II. The common-sense resolution to this "embarrassment of riches" is to set *AM* equal to the reported *AM*, rather than use the solution: $AM = GME\sqrt{GSD^{\ln GSD}}$ derived from the 6 simultaneous equations.

Estimation formulas for other data combinations in OEMD that include *N* are given in Table A-II.

Table A-I. Formulas for estimating summary statistics from expert judgments for *Min* and *Max* and from OEMD data for *Min, Max, AM* and *GM*.

Input values	**Estimate**	**Formula**
Method #0: v = 2 values, m = 2 equations (eqs. A2a & A2b), s = *2* semi-empiric parameters (α and ζ)		
Min & *Max*	$\widehat{GM}$ =	$GME \Big/ \left(\sqrt{Max/Min}\right)^{\bar{\alpha}}$ where $GME \equiv \sqrt{Max * Min}$
	$\widehat{GSD}$ =	$\left(\sqrt{Max/Min}\right)^{1/\bar{\zeta}}$
	$\widehat{AM}$ =	$\widehat{GM}\sqrt{\widehat{GSD}^{\widehat{GSD}}}$
	$\widehat{SD}$ =	$\frac{\widehat{AM}}{\widehat{GM}}\sqrt{\widehat{AM}^2 - \widehat{GM}^2}$
Method #1: v = 3 values, m = 3 equations (eqs. A2a, A2b & A5), s = 1 assumption (α= 0)		
Min, Max & *AM*	$\widehat{AM}$ =	AM
	$\widehat{z_{Max}}$ =	$\ln\left(Max/Min\right) \Big/ 2\sqrt{\ln\left[AM^2/\left(Min * Max\right)\right]}$
	$\widehat{GSD}$ =	$\left(\sqrt{Max/Min}\right)^{1/\widehat{z}_{Max}}$
	$\widehat{GM}$ =	$\mathrm{AM} \Big/ \sqrt{\widehat{GSD}^{\ln \widehat{GSD}}}$
	$\widehat{SD}$ =	$\frac{AM}{\widehat{GM}}\sqrt{AM^2 - \widehat{GM}^2}$
Method #2: v = 2 values, m = 3 equations, s = 2 = 1 assumption (α= 0) + 1 semi-empiric parameter (z_{Max})		
Min & *Max*	$\widehat{GM}$ =	GME
	$\widehat{GSD}$ =	$\left(\sqrt{Max/Min}\right)^{1/\overline{z_{Max}}}$
	$\widehat{AM}$ =	$\widehat{GM}\sqrt{\widehat{GSD}^{\widehat{GSD}}}$
	$\widehat{SD}$ =	$\frac{\widehat{AM}}{\widehat{GM}}\sqrt{\widehat{AM}^2 - \widehat{GM}^2}$
Method #3: v = 1 value, m = 3 equations, s = 3 = 1 assumption (α= 0) + 2 semi-empiric parameters (z_{Max} & *GSD*)		
*Max**	$\widehat{GM}$ =	$Max \Big/ \overline{GSD}^{\overline{z_{Max}}}$
	$\widehat{AM}$ =	$Max\sqrt{Q^{-2\overline{z_{Max}}}}$, where $Q = \overline{GSD}^{\ln \overline{GSD}}$
	$\widehat{GSD}$ =	$\overline{GSD}$
	$\widehat{SD}$ =	$\frac{\widehat{AM}}{\widehat{GM}}\sqrt{\widehat{AM}^2 - \widehat{GM}^2}$

Note: The formulas for the estimated statistics, designated by hats, are re-defined for each method. Therefore, applications of estimated statistics in subsequent formulas have values defined for the same method with the given set of input data. The only statistics whose values are the same in multiple methods are the central tendencies for z_{Max} and *GSD*, designated by bars.

*Formulas when *Min* is the only input are not given because this case does not occur in OEMD.

Table A-I. Concluded.

Input values	Estimate	Formula
Methods #4 and 5: v = 1 value (*AM* or *GM*), m = 1 equation (eq. A5), s = 1 semi-empiric parameter (*GSD* or Q)		
	$\widehat{AM}$ =	AM
AM	$\widehat{GM}$ =	$AM/\sqrt{Q}$
	$\widehat{GSD}$ =	$\overline{GSD}$
	$\widehat{SD}$ =	$\frac{AM}{\widehat{GM}}\sqrt{AM^2 - \widehat{GM}^2}$
	$\widehat{GM}$ =	GM
GM	$\widehat{AM}$ =	$GM\sqrt{Q}$
	$\widehat{GSD}$ =	$\overline{GSD}$
	$\widehat{SD}$ =	$\frac{\widehat{AM}}{GM}\sqrt{\widehat{AM}^2 - GM^2}$

Table A-II. Formulas for estimating summary statistics from OEMD data that include *N*.

Input values	Estimate	Formula
Method #1′: v = 5 values, m = 6 equations (eqs. A1a, A1b, A5, A8a, A8b & A9), s = -1 (over-determined solutions)		
N, *Min*, *Max* & *AM*	$\widehat{AM}$ =	AM or $GME\sqrt{\widehat{GSD}^{\widehat{GSD}}}$
	$\widehat{GSD}$ =	$\left(\sqrt{Max/Min}\right)^{1/E_N[z_{Max}]}$
	$\widehat{GM}$ =	GME or $\mathrm{AM} \Big/ \sqrt{\widehat{GSD}^{\ln \widehat{GSD}}}$
Method #2′: v = 4 values, m = 6 equations, s = 0 (exact solution)		
N, *Min* & *Max*	$\widehat{GM}$ =	GME
	$\widehat{GSD}$ =	$\left(\sqrt{Max/Min}\right)^{1/E_N[z_{Max}]}$
	$\widehat{AM}$ =	$\widehat{GM}\sqrt{\widehat{GSD}^{\widehat{GSD}}}$
Method #3′: v = 3 values, m = 6 equations, s = 1 semi-empiric parameters ($\overline{GSD}$)		
N & *Max*	$\widehat{GM}$ =	$Max \Big/ \overline{GSD}^{E_N[z_{Max}]}$
	$\widehat{AM}$ =	$Max\sqrt{Q^{-2E_N[z_{Max}]}}$, where $Q = \overline{GSD}^{\ln \overline{GSD}}$
	$\widehat{GSD}$ =	$\overline{GSD}$

Thus, for OEMD records with N, two alternative methods in Tables A-I and II provide estimates for the unknown summary statistics for OEMD data combinations #1, 2 and 3. Comparing methods in these two tables, their formulas are identical, except for the exponents of $\widehat{GSD}$ in methods 1 and 2 and the exponents of $\widehat{AM}$ and $\widehat{GM}$ in method 3. Those exponents contain $\widehat{z_{Max}}$ or $\overline{z_{Max}}$ in Table A-I, but are replaced with $E_N[z_{Max}]$ in Table A-II. Those exponents do not appear explicitly in methods 4 and 5.

In deciding which methods to use for the SEM calculations, we first note that methods in Table A-II have the additional assumption that the extreme quantiles for an OEMD record equal their expected values for the reported sample size N (eqs. A9). In order to evaluate the effects of this "expected quantile assumption," we used the Monte Carlo simulations described in the main paper. Those simulations take 10,000 samples of N measurements from a log-normal distribution with GM = 20 and GSD = 2.5, where N for each simulation is a random selection from all values in OEMD. From these simulated data, we calculated the overall uncertainty in the estimated summary statistics (as described in the Methods of the main paper) with the methods in Tables A-I and A-II. From the simulation results, we chose the methods with the lower overall uncertainty for the arithmetic and geometric means to use in the SEM calculations.

The resulting overall uncertainties for the two alternative exponents are given in Table A-III. The minimum uncertainty for the means are achieved with the exponent $E_N\,[z_{Max}]$ for methods #1 and 3, but with $\overline{z_{Max}}$ for method #2. These optimal exponents are used in the estimation formulas for both the SEM calculations (Table 1) and the validation calculations (Table 5).

Note that the uncertainty pattern for the standard deviations in Table A-III are somewhat different than for the means. In selecting the optimal methods, we focused on the mean estimates since only the SEM means are needed for obtaining risk estimates, which are INTEROCC's primary objectives. We included the uncertainties in the standard deviations in Table A-III and Table 5, so that they can be taken into account by any future studies of the variabilities and uncertainties in the risk estimates by simulations with the SEM.

Statistics for measurements outside the meter's dynamic range

The last type of record in OEMD are from studies which report measurements outside the meter's dynamic range. In these cases, *Min* or *Max* are replaced with the dynamic range's lower limit (ODR*Min*) or upper limit (ODR*Max*). In those cases, we model the actual *Min* or *Max* with the reported ODR values times empirical parameters $k_{under} < 1$ and $k_{over} > 1$:

$$\widehat{Min} = ODRMin * \widehat{k_{under}} \tag{A11a}$$

$$\widehat{Max} = ODRMax * \widehat{k_{over}} \tag{A11b}$$

Initially, we were able to calculate an average k_{over} empirically based on data from two sets of measurements of personal exposures to a magnetic field source using two different ENERTECH EMF

Table A-III. Simulated uncertainties of the alternative estimation formulas in Tables A-I and A-II with the lower uncertainty for each combination of the estimated statistic and method in **bold**.

Estimated statistic	**Exponent alternatives***	**Overall uncertainty of the estimated statistics by method # (with the OEMD statistics used)**		
		1(AM, *Min & Max*)	**2(*Min & Max*)**	**3(*Max*)**
$\widehat{GM}$	z_{Max}	51%	**53%**	212%
	$E_N[z_{Max}]$	**47%**	**53%**	**143%**
$\widehat{AM}$	z_{Max}		**125%**	166%
	$E_N[z_{Max}]$		682%	**88%**
$\widehat{GSD}$	z_{Max}	75%	75%	**78%**
	$E_N[z_{Max}]$	**33%**	**33%**	**78%**
$\widehat{SD}$	z_{Max}	**185%**	**593%**	**894%**
	$E_N[z_{Max}]$	1793%	262,450%	2098%

*In the simulations, these alternatives were used as $\widehat{z_{Max}}$ for estimation method #1, and as $\overline{z_{Max}}$ in methods #2 and 3.

meters (http://www.enertech.net), a Standard EMDEX II (*ODRMax*=300 μT) and a Hi-Field EMDEX II (*ODRMax* = 12,000 μT). However, no such data were available for EMF measurements below a meter's limit of detection, so we needed a semi-empirical approach to obtain k_{under}. We identified two suitable methods by using the same assumptions (a log-normal distribution and $\alpha = 0$) and similar algebra to the derivations above.

In the first approach, the input data are ODR*Min* and *Max*, so eqs. A1 and A11a are adequate to derive k_{under} with the semi-empirical methods described above. The m=2 simultaneous equations are:

$$lnODRMin + ln\widehat{k_{under}} = ln\widehat{GM} - \widehat{z_{Max}}ln\widehat{GSD} \tag{A12a}$$

$$lnMax = ln\widehat{GM} + \widehat{z_{Max}}ln\widehat{GSD} \tag{A12b}$$

These equations have a total of t = 6 variables of which v = 2 have values, so they can be solved for the summary statistics with s = 2 semi-empiric values for z_{Max} and *GSD*.

$$\widehat{k_{over}} = \frac{Max}{ODRMin * \overline{GSD}^{\overline{z_{\text{Max}}}}} \tag{A13a}$$

$$\widehat{GM} = \sqrt{\widehat{k_{under}} * ODRMin * Max} \tag{A13b}$$

This approach gives specific values for k_{under} with each OEMD record reporting ODR*Min*, but the results for k_{under} were often greater than 1, a violation of the model's assumptions and therefore implausible.

In the second approach, a sub-set of the ODRMin records were used that also have a value for *AM*. By adding eq. A5 to the set of simultaneous equations (eq. A12), we derive a different formula for k_{under} with only one semi-empirical parameter as follows:

Add eqs. A12a and A12b, and re-arrange to give:

$$ln\widehat{GM} = \frac{1}{2}\left(lnMax + ln\widehat{k_{under}} + lnODRMin\right) \tag{A14}$$

Now, substitute eq. A14 for ln *GM* in eq. A5, use the semi-empirical parameter $\overline{GSD}$, solve for ln k_{under}, and take the anti-log to obtain the desired result:

$$\widehat{k_{under}} = \frac{AM^2}{Max * ODRMin * \sqrt{Q}} \tag{A15}$$

With this approach, the mean of k_{under} over the sub-set is less than one, which allows for realistic estimates of the GM for each ODR*Min* record from the ODR equivalent of the *GME* (eq. A4):

$$\widehat{GM} = \sqrt{\overline{k_{under}} * ODRMin * Max} \tag{A16}$$

The other statistics for these ODR*Min* records are then calculated with analogs of the $m = 2$ formulas in Table A-I. The resulting formulas are reported in Table 2 in the main paper.

B. Confidence-Weighted Means and Standard Deviations for the SEM

For each source in OEMD, the exposure statistics AM_i, SD_i, GM_i and GSD_i for all applicable records i are pooled with confidence weights C_i. To derive formulas for the confidence-weighted means and standard deviations from the summary statistics for individual records, we start with general formulas for the weighted arithmetic mean and unbiased weighted sample standard deviation in terms of the primary data x_k and non-random weights w_k (a.k.a "reliability weights" (Harrel et al., 2015) :

$$ {}_{w}AM = \sum_k w_k x_k \Big/ \sum_k w_k $$

$$ {}_{w}SD^2 = \frac{\sum_k w_k \left(x_k - wAM\right)^2}{\sum_k w_k - \left(\sum_k w_k^2 \Big/ \sum_k w_k\right)} $$

In our derivation of the confidence weighted statistics, we next group the primary data x_k (which is seldom present in OEMD) by their record i, so that their k indices are renumbered as follows:

$i =$	1	2	….	i	….
$j =$	$1, 2 \ldots N_1$	$1, 2 \ldots N_2$	….	$1, 2 \ldots N_i$	….

Since the same confidence weight C_i for a given record i is applied to all the primary data x_{ij} in that record, the confidence weighted statistics are:

$$ \begin{aligned} {}_{cw}AM &= \sum_i C_i \sum_{j=1}^{N_i} x_{ij} \Big/ \sum_i \sum_{j=1}^{N_i} C_i \\ &= \sum_i C_i \sum_{j=1}^{N_i} x_{ij} \Big/ \sum_i C_i N_i \end{aligned} \tag{A17a} $$

$$ {}_{cw}SD^2 = \frac{\sum_i C_i \sum_{i=1}^{N_i} \left(x_{ij} - {}_{cw}AM\right)^2}{\sum_i C_i N_i - \left(\sum_i C_i^2 N_i \Big/ \sum_i C_i N_i\right)} \tag{A17b} $$

Now the summary statistics written in terms of the primary data are:

$$AM_i = \frac{1}{N_i}\sum_j x_{ij} \tag{A18a}$$

$$SD_i^2 = \frac{\sum_{j=1}^{N_i}\left(x_{ij} - AM_j\right)^2}{N_i - 1} = \frac{\sum_j x_{ij}^2 - N_i AM_i^2}{N_i - 1} \tag{A18b}$$

So they can be re-arranged as:

$$\sum_j x_{ij} = N_i AM_i \tag{A19a}$$

$$\sum_j x_{ij}^2 = \left(N_i - 1\right)SD_i^2 + N_i AM_i^2 \tag{A19b}$$

Now, eq. A19a can be substituted into eq. A17a in order to obtain the desired formula for the confidence weighted AM in terms of its component exposure AMs:

$${}_{cw}AM = \sum_i C_i N_i AM_i \Big/ \sum_i C_i N_i \tag{A20}$$

To obtain the equivalent results for the confidence weighted SD, expand the numerator of eq. A17b:

$${}_{cw}SD^2 = \frac{\sum_{i,j} C_i {x_{ij}}^2 - 2\,{}_{cw}AM \sum_{i,j} C_i x_{ij} + {}_{cw}AM^2 \sum_i C_i N_i}{\sum_i C_i N_i - \left(\sum_i C_i^2 N_i \Big/ \sum_i C_i N_i\right)}$$

to get:

$${}_{cw}SD^2 = \frac{\sum_i C_i \sum_j {x_{ij}}^2 - {}_{cw}AM^2 \sum_i C_i N_i}{\sum_i C_i N_i - \left(\sum_i C_i^2 N_i \Big/ \sum_i C_i N_i\right)}$$

where eq. A19 was used.

Finally substitute eq. A18b to obtain the desired formula:

$$_{cw}SD^2 = \frac{\sum_i C_i \left[\left(N_i - 1 \right) SD_i^2 + N_i \left(AM_i^2 - {}_{cw}AM^2 \right) \right]}{\sum_i C_i N_i - \left(\sum_i C_i^2 N_i \Big/ \sum_i C_i N_i \right)} \tag{A21}$$

To obtain the confidence weighted geometric means and standard deviations, start with the log-transforms of eqs. A17 and A18:

$$\ln {}_{cw}GM = \sum_{i,j} C_i y_{ij} \Big/ \sum_i C_i N_i$$

$$\ln^2 {}_{cw}GSD = \frac{\sum_i C_i \sum_{i=1}^{N_i} \left(y_{ij} - \ln {}_{cw}GM \right)^2}{\sum_i C_i N_i - \left(\sum_i C_i^2 N_i \Big/ \sum_i C_i N_i \right)}$$

$$\ln GM_i = \frac{1}{N_i} \sum_j y_{ij}$$

$$\ln^2 \mathrm{GSD_i} = \frac{\sum_j \mathrm{y_{ij}^2} - \mathrm{N_i} \ln^2 \mathrm{GM_i}}{\mathrm{N_i} - 1}$$

where $y_{\mathrm{ij}} = \ln x_{\mathrm{ij}}$.

Following the same procedures as above, the desired formulas are quickly obtained:

$$\ln {}_{cw}GM = \sum_i C_i N_i \ln GM_i \Big/ \sum_i C_i N_i \tag{A22}$$

$$\ln^2 {}_{cw}GSD = \frac{\sum_i C_i \left[\left(N_i - 1 \right) \ln^2 GSD_i + N_i \left(\ln^2 GM_i - \ln^2 {}_{cw}GM \right) \right]}{\sum_i C_i N_i - \left(\sum_i C_i^2 N_i \Big/ \sum_i C_i N_i \right)} \tag{A23}$$

Q.E.D.

Finally, note that these pooling formulas (eqs. A20 – A23) can work correctly with OEMD records with a single measurement x_i ($N_i = 1$) if their summary statistics are treated appropriately. From the definitions above of the arithmetic and geometric means, $x_i = AM_{\mathrm{i}} = GM_i$ when $N_i = 1$. By making these substitutions for N_i = 1 records, eqs. A20 and A22 correctly calculate the confidence weighted means.

The values of the standard deviations for N_i =1 records are arbitrary since their contributions to the pooling formulas (eqs. A21 and A23) are:

$$(N_i - 1)\ SD_{\mathrm{i}}^2 = (N_i - 1)\ \ln^2 GSD_i = 0$$

For convenience in our SEM calculations, we set SD_{i} = 0 and GSD_{i} = 1 for N_{i} = 1 records, so they work correctly with the confidence-weighted variance formulas.

The degrees of freedom for the reliability-weighted variance (Harrel et al., 2015) is easily converted to the confidence-weighted degrees of freedom: ${}_{cw}df = \sum_i C_i N_i - \left(\sum_i C_i^2 N_i \Big/ \sum_i C_i N_i \right)$. Before ${}_{cw}df$ can be used to calculate 95% confidence limits on the confidence-weighted means, a comprehensive uncertainty measure should be derived by combining ${}_{cw}SD$ and ${}_{cw}GSD$ (representing the uncertainty from sample sizes N_i, the quality factors in C_i , and the within-source variability) with the uncertainties in our semi-empiric estimates of the summary means (Table 5).

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