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Validity of at home model predictions as a proxy for personal exposure to radiofrequency electromagnetic fields from mobile phone base stations

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ABSTRACT

Background: Epidemiological studies on the potential health effects of RF-EMF from mobile phone base stations require efficient and accurate exposure assessment methods. Previous studies have demonstrated that the 3D geospatial model NISMap is able to rank locations by indoor and outdoor RF-EMF exposure levels. This study extends on previous work by evaluating the suitability of using NISMap to estimate indoor RF-EMF exposure levels at home as a proxy for personal exposure to RF-EMF from mobile phone base stations.
Methods: For 93 individuals in the Netherlands we measured personal exposure to RF-EMF from mobile phone base stations during a 24 h period using an EME-SPY 121 exposimeter. Each individual kept a diary from which we extracted the time spent at home and in the bedroom. We used NISMap to model exposure at the home address of the participant (at bedroom height). We then compared model predictions with measurements for the 24 h period, when at home, and in the bedroom by the Spearman correlation coefficient (r_{sp}) and by calculating specificity and sensitivity using the 90th percentile of the exposure distribution as a cutpoint for high exposure.
Results: We found a low to moderate r_{sp} of 0.36 for the 24 h period, 0.51 for measurements at home, and 0.41 for measurements in the bedroom. The specificity was high (0.9) but with a low sensitivity (0.3).
Discussion: These results indicate that a meaningful ranking of personal RF-EMF can be achieved, even though the correlation between model predictions and 24 h personal RF-EMF measurements is lower than with at home measurements. However, the use of at home RF-EMF field predictions from mobile phone base stations in epidemiological studies leads to significant exposure misclassification that will result in a loss of statistical power to detect health effects.

1. Introduction

There is ongoing concern about the potential health effects of exposure to radiofrequency electromagnetic fields (RF-EMF) from mobile phone base stations (European Commission, 2010). Epidemiological studies to date have found only very limited evidence for any kind of health effects related to RF-EMF (Röösli et al., 2010). However, uncertainties in the exposure assessment of personal RF-EMF (from all sources and sources separately) hinder reaching a more definitive conclusion about the absence or presence of any possible association between RF-EMF exposure, from for example mobile phone base stations, and health problems.

RF-EMF exposure from mobile phone base stations (in the Netherlands) contributes ~13% to total environmental RF-EMF exposure (Bolte and Eikelboom, 2012). This contribution may vary by location and by age groups due to differences in behavioural patterns. There is no scientific evidence for any specific biological mechanisms leading to health effects, and thus potential health

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effects of RF-EMF may differ across frequency bands. Therefore, it is important to study the exposure from mobile phone base stations both separately and combined. Due to the absence of a strong correlation between RF-EMF from mobile phone base stations and other RF-EMF sources (Frei et al., 2010) it is possible to study this source separately.

Several methods have been employed to assess individual exposure to RF-EMF from mobile phone base stations. Personal measurements are considered the best approach in assessing personal RF-EMF exposure (Neubauer et al., 2007). However, even the use of personal dosimeters has limitations that can lead to underestimation of exposure, such as body shielding, measuring multiple signals in one frequency band, and measurements below the detection limit (Bolte et al., 2011; Lauer et al., 2012). Further, because of time and cost constraints personal measurements are not feasible for large scale epidemiological investigations (Frei et al., 2010). Other methods typically estimate exposure at the home address as a proxy of personal exposure. Simple methods such as the distance between nearby transmitters and the home address as a proxy of personal exposure to RF-EMF (Blettner et al., 2009; Dode et al., 2011; Eskander et al., 2012) are insufficiently accurate (Frei et al., 2010; Neitzke et al., 2007). Frei et al. (2010) showed that using a model to estimate exposure at the home address is currently the most appropriate method for estimating RF-EMF exposure in large epidemiological studies. In recent years several geospatial models have been developed for estimating RF-EMF exposure from mobile phone base stations at the home address (Briggs et al., 2012; Bürgi et al., 2008; Neitzke et al., 2007).

The 3D radiowave propagation model NISMap (Bürgi et al., 2008) has been developed to predict RF-EMF exposure from fixed site transmitters. Previous studies (Beekhuizen et al., 2013; Beekhuizen et al., 2014b; Bürgi et al., 2010, 2008) have shown that NISMap is able to meaningful rank outdoor and indoor RF-EMF exposure levels from mobile phone base-stations. Spearman correlations for total mobile phone downlink (hereafter referred to as downlink) RF-EMF between predicted values and spot measurements were around $r_{sp}=0.7$. However, people are not always at their home address, and the amount of time they spend at home can vary between individuals and different time periods (Brasche and Bischof, 2005; Farrow et al., 1997). Therefore, a model estimating RF-EMF for the home address may not be sufficiently accurate to predict personal exposure to RF-EMF from base stations. Limited work has been done to validate the estimation of personal RF-EMF exposure from base-stations based on spatial models. Frei et al. (2009) measured personal exposure during one week for 166 subjects in Switzerland. They compared personal RF-EMF exposure measurements from all far field sources (including FM, TV, Tetrapol, mobile phone uplink (hereafter referred to as uplink), downlink, DECT, W-LAN) with NISMap model predictions of exposure to fixed site transmitters (FM, TV, Tetrapol, mobile phone base station downlink). They reported a Spearman correlation of 0.28 (CI 95%: 0.14–0.42) between measured and modelled values (Frei et al., 2010). As in the end health effects are driven by the individual exposure experience there is a clear need for additional studies on the suitability of using at home modelling of RF-EMF for approximating personal exposure to RF-EMF from base stations. In this study we extend on previous observations by evaluating whether at home modelled RF-EMF exposure by NISMap has a good correlation with personal measurements, and whether it is a valid proxy for 24 h personal exposure to RF-EMF from base stations.

2. Material and methods

2.1. Population

The selection method and exclusions are described in more detail in Bolte and Eikelboom (2012). In short, we invited 3000 adult (18+) members from an internet panel (TNS-Nipo) living in the north-west of the Netherlands. The panel members were approached by email to fill out a questionnaire and carry a measurement device for 24 h. This resulted in a positive response of 909 persons from which 140 were selected (based on variation in features such as sex, age, social economic status, employment and residential area) to participate in the measurements. The measurements took place in 2009 and 2010 and continued until 100 complete measurement datasets were collected. After excluding participants with incomplete diary data, 98 participants with complete measurement data were retained (age range: 18–82). Five participants were excluded because we could not estimate the field strength for their home address due to missing input data, resulting in a total of 93 participants with both model estimates as well as personal measurements.

2.2. Model description and model input

For each participant we estimated RF-EMF exposure at the home address (at bedroom height) using the NISMap model. We did not model the exposure at work, as subjects in general spend less than 30% of their time at work and because the work address was not known for all participants. Additionally, some of the participants have professions that are not bound to one location, f.i. driver or builder.

NISMap is a three dimensional radiowave propagation model that uses detailed information about antenna location and radiation patterns, 3D building data and topography to compute the field strength of the downlink sources of different frequencies (UMTS, GSM900, GSM1800). The Double Power Law (ITU, 2009) radio wave propagation algorithm used previously by Bürgi et al. (2010) and Beekhuizen et al. (2013, 2014b) was used to calculate the decrease of RF-EMF with distance. NISMap allows to set building damping values to correct for the attenuation of radio waves by buildings. We set the damping of roofs to 4.5 dB, damping of walls to 3 dB and the inside damping to 0.6 dB/m for all buildings. These values are similar to values used in earlier studies (Beekhuizen et al., 2013, 2014b; Bürgi et al., 2010). Individual building characteristics such as the type of wall material were not used as input data for the model, as a previous study found that inclusion of these predictors did not significantly improve model prediction in the Netherlands most likely because of the relative homogenous building characteristics (Beekhuizen et al., 2014b). A technical description of the model can be found in Bürgi et al. (2008, 2010).

The coordinates of the participants' home addresses were obtained from the Dutch Cadastre in 2012 (BAG, Basisregistraties Adressen en Gebouwen). The Dutch Radiocommunications Agency (Agentschap Telecom) provided us with detailed information about transmitters (2011), such as the coordinates, beam direction, and height of the transmitter. We created a 3D box model of all buildings in the Netherlands, by combining data on the building locations and outline from the national BAG building data set with height information from the Netherlands elevation model (Actueel Hoogtebestand Nederland 2, AHN2). The bedroom height was used as input for the model, as participants generally spend most of their time in their bedroom while they are at home. To obtain the bedroom height we asked participants the floor number of their bedroom (where ground level counts as zero). We assumed a floor height of 3 m per floor. If this resulted in an estimation of the bedroom height larger than the total building height ($n=5$) we subtracted 1.5 m from the total building height and used that value as an estimate of bedroom height.

2.3. Exposure assessment

We used the EME-spy 121 (Satimo, Cortaboeuf, France, http://www.satimo.fr) to measure the RF electric fields in 12 frequency bands (FM radio (88–108 MHz), TV3 (174–233 MHz), TETRA (380–400 MHz), TV4&5 (470–830 MHz), GSM 900 uplink (880–915 MHz), GSM 900 downlink (925–960 MHz), GSM 1800 uplink (1710–1785 MHz), GSM 1800 downlink (1805–1880 MHz), DECT (1880–1900 MHz), UMTS uplink (1920–1980 MHz), UMTS downlink (2110–2170 MHz), WiFi (2400–2500 MHz)), with the sampling frequency set to every 10th second. The upper detection limit of the device is 265 mW/m^2 (10 V/m). The lower detection limit is 0.0066 mW/m^2 (0.05 V/m).

Participants were asked to carry the measurement set continuously for 24 h, except when they were sleeping or during activities where it would not be safe for the participant to wear the device or the device would be at risk of being damaged (such as showering, sports). Participants carried the EME-SPY in a camera bag strapped over their left shoulder and clipped on the right hip to the belt. At night the exposimeter was positioned on the bedside table next to the head, with the blue side, containing the antennae, directed towards the window.

Participants filled in a time activity diary, where they described their activities during the measurements, including mobile/cordless phone use, as well as all unexpected or notable events such as not being able to wear the measurement set during a specific time window. More information about the exact procedure can be found in Bolte and Eikelboom (2012).

2.4. Data-analysis

A calibration correction for each exposimeter was applied to all measurements, based on calibration tests in a GTEM (Gigahertz Transverse ElectroMagnetic cell) and an Open Area Test site (Bolte et al., 2011). Downlink measurements may be slightly influenced by out-of-band signals such as DECT (Bolte et al., 2011). We therefore removed the measurements during time spent on DECT cordless phones. We then computed the total downlink exposure by summing power density (W/m^2) of the GSM900 downlink, GSM1800 downlink and UMTS downlink frequencies for the measurements and the model predictions (results per downlink frequency in Appendix, Table A.1). In order to validate the predictions of the NISMap model, we only analysed measured and modelled RF-EMF downlink exposure from mobile phone base stations. Based on the activity diary, all measurement data were placed in three different categories: in bedroom, at home, overall 24 h. Statistics per category (bedroom/at home/overall 24 h) were calculated by pooling all available measurements per category.

Because the detection limit of the exposimeter is relatively high compared to exposure values in a home environment there was a large percentage (GSM900 83%, GSM1800 90%, UMTS 96%, total downlink 78%) of measurement data below the detection limit. We used robust regression on order statistics (ROS) to impute measurement values below the detection limit, which has been shown to be an reliable method for this type of data (Röösli et al., 2008).

We computed several indicators to determine the accuracy of the NISMap model predictions: the mean modelled and measured values, the ratio (mean modelled value divided by the mean measured value), the mean difference between modelled and measured values (modelled-measured), the mean relative difference (mean difference divided by the average of measured and modelled values), precision (the standard deviation of differences between modelled and measured values), the coefficient of variation (ratio of the standard deviation to the mean) and the Spearman rank correlation (r_{sp}) between modelled and measured values. In order to calculate sensitivity and specificity parameters we dichotomized the modelled and measured values with a cutoff percentile of 90% based on distributional plots. All analyses were carried out using the statistical program R (3.1.0).

3. Results

3.1. Descriptive statistics

The mean age of the 93 participants, 45 men and 48 women, was 44.3 years (range: 19–81, standard deviation: 16.2). Participants spent on average 16.8 (standard deviation: 3.9) h at home, of which 7.3 h (standard deviation: 1.93) in the bedroom. The majority of participants did not work on the day of the measurements (worked: $n=36$, not worked: $n=57$). There was a large variation in home types (detached/semi-detached home: $n=25$, terraced home: $n=28$, large apartment: $n=15$, small apartment: $n=25$) as well as degree of urbanisation (downtown urban area: $n=21$, urban outskirts: $n=27$, urban green area: $n=17$, village: $n=28$).

3.2. Accuracy of model predictions

Table 1 shows the accuracy of the model predictions (see appendix Table A.1 for results per frequency band). The mean modelled value for the 24 h period was 0.039 mW/m^2, the mean measured value 0.023 mW/m^2. We found a Spearman correlation of 0.36 between modelled and measured values for the 24 h period. The statistics restricted for time spent at home (mean measured: 0.017 mW/m^2) and time spent in the bedroom (mean measured: 0.018 mW/m^2) were similar but with somewhat higher Spearman correlations (at home $r_{sp}=0.51$; bedroom $r_{sp}=0.41$). The sensitivity of the model predictions for the total 24 h period was 0.30 (CI 95%=0.07–0.65), the specificity of the model predictions was 0.92 (CI 95%=0.83–0.97). In Fig. 1 we show two Bland–Altman plots (Bland and Altman, 1986) for the absolute and the relative differences between the NISMap model predictions and the 24 h overall measurements. We observe large differences

Table 1
Accuracy of model predictions for the total downlink RF-EMF of all mobile phone base stations (unit: mW/m^2) for the 24 h period, time spent at home and in the bedroom.

	24 h Overall	At home	In bedroom
Mean modelled[a]	0.039	0.039	0.039
Mean measured	0.023	0.017	0.018
Ratio model/measured	1.713	2.356	2.212
Median measured	0.011	0.004	0.000
Mean difference (modelled-measured)	0.016	0.022	0.021
Mean relative difference	0.525	0.808	0.755
Precision (sd difference)	0.102	0.102	0.099
Coefficient of variation	4.470	6.129	5.572
Spearman R	0.36	0.51	0.41
Sensitivity 90% cutoff and 95% confidence intervals	0.30 (0.07–0.65)	0.30 (0.07–0.65)	0.40 (0.12–0.74)
Specificity 90% cutoff and 95% confidence intervals	0.92 (0.83–0.97)	0.92 (0.83–0.97)	0.93 (0.85–0.97)

[a] This value is equal for each category because we only model exposure for the home address at bedroom height.

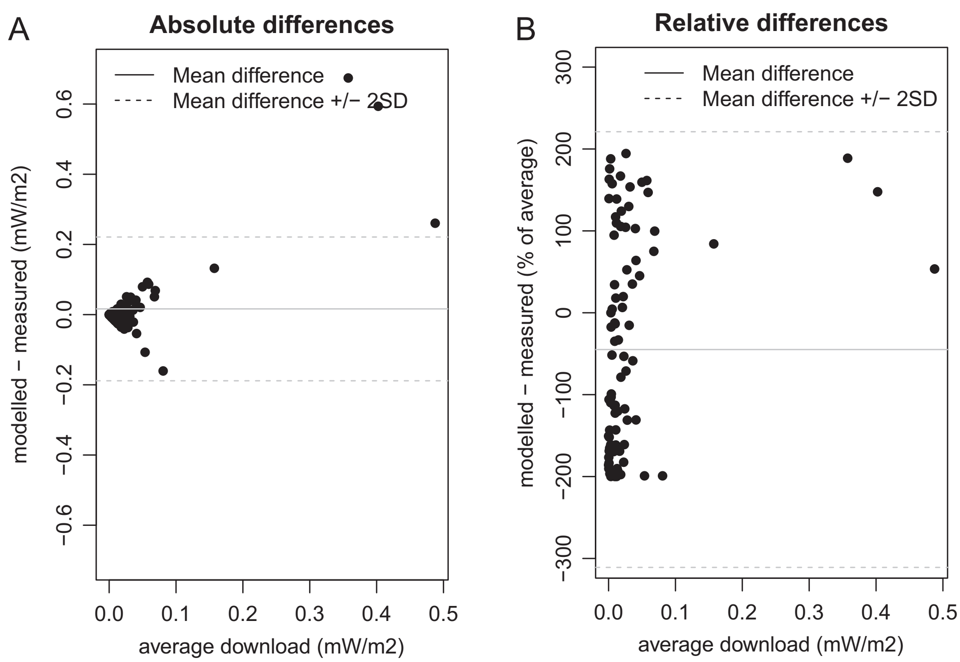

Fig. 1. Bland–Altman plot of the mean downlink RF-EMF, showing the absolute (A. left) and relative (B. right) differences between modelled and measured values for the 24 h period. The solid line shows the bias and the striped lines the bias ± 2 standard deviations.

between modelled and measured RF-EMF levels, with both an over- and underestimation. However, on average there is indication of an overestimation of the model of the absolute levels (Table 1, Fig. 1B). An extra analysis where we stratified by the subjects that did not work during the measurement data ($n=57$) and subjects that did work during the measurement day showed a slightly higher Spearman correlation for subjects who did not work (not worked: $r_{sp}=0.39$, worked: $r_{sp}=0.32$).

4. Discussion

In this study we evaluated the validity of using the at home exposure (at bedroom height) as modelled by NISMap to assess personal exposure to RF-EMF in epidemiological studies. We compared NISMap model predictions of RF-EMF exposure from mobile phone base stations with personal measurements (downlink). We found a low to moderate Spearman correlation between model predictions and personal measurements of 0.36 for a 24 h period. As expected, these correlations are lower than correlations between model predictions at home (r_{sp} 0.51) and in the bedroom (r_{sp} 0.41).

In epidemiological studies it is important to be able distinguish between high and low exposed individuals. In our study we used the sensitivity and the specificity to evaluate how well we distinguish between exposed and non-exposed individuals (as defined by the 90th percentile of the empirical distribution). We found a high specificity (0.9) of the NISMap model, but a relatively low sensitivity (0.3). An ideal model would have a high specificity as well as a high sensitivity. However, for epidemiological studies with rare exposures, such as high exposure to RF-EMF, a high specificity is more important than a high sensitivity. Neubauer et al. (2007) have demonstrated that, if an association exists, low specificity leads to a greater risk bias and therefore less power to detect potential health effects. The effect of low sensitivity on the risk bias is much smaller.

Frei et al. (2010) also assessed the performance of the NISMap model in predicting personal RF-EMF exposure in Switzerland. Frei and colleagues modelled all fixed site transmitters (FM, TV, Tetrapol, and Downlink) and compared this with measurements from all far field sources (FM, TV, Tetrapol, uplink, Downlink, DECT, W-LAN). Compared to our study they reported a slightly lower correlation of $r_{sp}=0.28$. This might in part be explained due the fact that the comparison of Frei et al. included more RF-EMF sources in their measurements than that were used in the NISMap model. Similarly, when we compared our modelled downlink exposures to the personal measurements including all far field exposures, we obtained a correlation of $r_{sp}=0.22$.

The studies by Bürgi et al. (2010) and Beekhuizen et al. (2014b) focused on downlink RF-EMF levels only. They compared indoor spot measurements with NISMap predictions and found Spearman correlations between 0.60 and 0.74. These values are noticeably higher than our indoor values based on personal measurements (bedroom r_{sp} 0.41; at home r_{sp} 0.51). Possible explanations might be the higher detection limit of the measurement device used in our study as well as differences in measurement method. Our subjects carried a dosimeter on their bodies and left the device on a small bedside table during nighttime. In contrast, both other studies (Beekhuizen et al., 2014b; Bürgi et al., 2010) used stationary spot measurements on 7 spots in the room, thereby capturing the average exposure in the room. While our method may reflect personal exposure more accurately, our measurement results could be influenced strongly by local interference patterns.

The specificity (0.90) reported in Bürgi et al. (2010) is similar to our specificity for the at home measurements (0.92), although they reported a higher sensitivity (0.60 versus 0.32 in our study). These results indicate that modelling bedroom exposure at the home address as a proxy for personal exposure does not lead to a large number of ‘false positives’ (subjects incorrectly classified as high exposed), which is an important feature for epidemiological studies with a low prevalence of (high) exposure. However, because of the low sensitivity it will take a large sample size to detect potential health effects if they exist.

4.1. Strengths and limitations

One of the strengths of our study is the varied subject sample. The subjects vary greatly considering age, sex, employment, residential area and housing characteristics. A second strength is the detailed input data on antenna characteristics, 3D buildings and elevation used to predict exposure, as accurate and complete input data is important for the spatial modelling of RF-EMF levels (Beekhuizen et al., 2015, 2014a). Another strength of our study is the knowledge about the whereabouts of the subjects allowing us to compare separately between the measured exposure when at home and when in the bedroom.

One of the limitations in validation studies is the lack of a "golden standard" for estimating error in model predictions. In our study we compare model predictions to personal measurements, but even personal measurements are not a perfect reflection of true exposure. The EME Spy 121 measurement device underestimates actual exposure (Bolte et al., 2011) and has a relatively high lower detection limit. Due to the large number of measurements below the detection limit our results are highly dependent on the ROS modelling. However, it has been shown that ROS is a reliable imputation method for this type of data. Röösli et al. (2008) and we therefore do not expect that the large number of non-detects influenced our results. Secondly, we estimated bedroom height using a rough estimate of an average floor height of 3 m per floor multiplied with the floor number of the bedroom, leading to some error in the exact receptor height. An accurate estimation of the height is however very important for the accuracy of the model estimation (Beekhuizen et al., 2014a) and this may have led to a decrease in model performance. Finally, for this study we used antenna data from 2011 as input data for the prediction model. The measurements were taken earlier, in 2009 and 2010. For an optimal comparison the information about location and characteristics of the antenna should be dated as closely to the date of the measurements as possible.

4.2. Considerations for future research

The use of models to predict personal exposure to RF-EMF has limitations due to the large spatial variation in RF-EMF levels in combination with subject movement patterns. Misclassification can lead to significant problems in epidemiological studies that look at an association between RF-EMF exposure and possible health effects, as potential health effects might not be detected due to lack of power and attenuated effect sizes. However, there are currently no alternatives for geospatial models to predict exposure for large scale epidemiological studies. Some improvements might be made by modelling additional locations where participants spend a lot of time like work or school, but future studies are necessary to assess the potential added value of this approach. It should be noted that detailed location information of the participants within buildings such as schools and offices are needed to reliable model RF-EMF exposure due to the large spatial variation in RF-EMF levels. This information is often not readily available, making it difficult to include these locations in estimating total exposure. When we stratified our analyses by the subjects that did not work during the measurement data ($n=57$) and subjects that did work during the measurement day we observed a slightly higher Spearman correlation for subjects who didn't work (not worked: $r_{sp}=0.39$, worked: $r_{sp}=0.32$). Note that the low to moderate association between modelled exposure to RF-EMF from mobile phone base stations and measured personal exposure is similar to the accuracy found for other environmental pollutants, most notably air pollution (e.g. Nethery et al. 2008; Van Roosbroeck et al. 2008). Despite the presence of misclassification, a large number of air pollution studies have found health effects, although the type of exposure and health effects expected for air pollution are very different than for RF-EMF. When epidemiological studies have a sufficient sample size it should be possible to pick up potential health effects of RF-EMF exposure using NISMap.

4.3. Conclusion

This study evaluated the use of NISMap to predict personal exposure to RF-EMF from mobile phone base stations. The results indicate that a meaningful ranking of personal RF-EMF can be achieved, even though the correlation between model predictions and 24 h personal RF-EMF measurements is lower than with at home measurements. Our results indicate significant misclassification of participants, although in part our low Spearman correlations and sensitivity parameters can be explained by the inherent measurement error in the personal RF-EMF measurements. Exposure misclassification, assuming a classical error structure, leads to loss of power and can lead to attenuation of effect sizes (Armstrong, 1998). The main implication of our findings is therefore that epidemiological studies of health risks from far field RF-EMF will need a large number of participants in order to have sufficient power for detecting potential health effects. Ideally we would use more accurate methods of exposure assessment, but such methods (personal measurements, modelling multiple locations where the participants spend a lot of time, or including behavioural characteristics and other RF-EMF sources in the exposure model) are often expensive or require information that is not readily available.

Disclosure

The authors declare no conflicts of interest.

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The Medical Ethics Committee of the University Medical Center Utrecht approved the study protocol. A copy of the approval letter is included in the submitted files.

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Appendix A

See Appendix Table A1

Table A.1
Accuracy of model predictions for GSM, DCS, UMTS and total downlink RF-EMF of all mobile phone base stations (unit: mW/m^2) for 24 h overall, time spent at home, and in the bedroom.

	24 h Overall				At home				In bedroom			
	GSM	DCS	UMTS	Total downlink	GSM	DCS	UMTS	Total downlink	GSM	DCS	UMTS	Total downlink
Mean modelled	0.017	0.015	0.007	0.039	0.017	0.015	0.007	0.039	0.017	0.015	0.007	0.039
Mean measured	0.007	0.014	0.002	0.023	0.006	0.010	0.001	0.017	0.006	0.011	0.001	0.018
Ratio modelled/measured	2.405	1.068	4.227	1.712	2.981	1.536	6.346	2.356	2.969	1.408	5.548	2.122
Median measured	0.003	0.004	0.001	0.011	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000
Mean difference (modelled-measured)	0.010	0.001	0.005	0.016	0.011	0.005	0.006	0.023	0.011	0.004	0.006	0.022
Mean relative difference	0.825	0.065	1.235	0.525	0.995	0.423	1.455	0.808	0.992	0.339	1.389	0.755
Precision (SD difference)	0.075	0.053	0.018	0.102	0.074	0.054	0.018	0.102	0.073	0.058	0.017	0.099
Coefficient of variation	10.558	3.770	10.804	4.470	13.038	5.452	15.990	6.129	12.805	5.365	12.943	5.572
Spearman R	0.323	0.269	0.173	0.361	0.426	0.522	0.428	0.511	0.413	0.327	0.362	0.410

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