Science of the Total Environment 550 (2016) 987–993

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Residential exposure to RF-EMF from mobile phone base stations: Model predictions versus personal and home measurements

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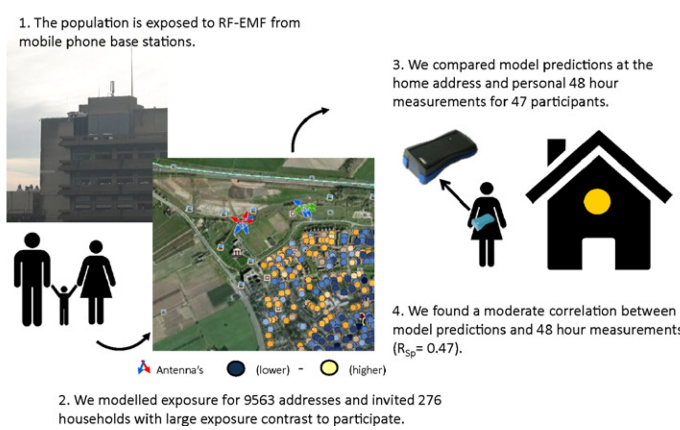
HIGHLIGHTS

- There is public concern about exposure to RF-EMF from mobile phone base stations.
- Accurate and efficient exposure assessment is required for epidemiological studies.
- At home model predictions of RF-EMF are used as a proxy of personal exposure.
- We compared home address model predictions with 48 h personal measurements.
- Model estimations at the home address provide a meaningful ranking of personal RF-EMF.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 9 November 2015
Received in revised form 13 January 2016
Accepted 28 January 2016
Available online 4 February 2016

Editor: D. Barcelo

Keywords:
Electromagnetic fields
RF-EMF
Exposure assessment
Geospatial model

ABSTRACT

Introduction: Geospatial models have been demonstrated to reliably and efficiently estimate RF-EMF exposure from mobile phone base stations (downlink) at stationary locations with the implicit assumption that this reflects personal exposure. In this study we evaluated whether RF-EMF model predictions at the home address are a good proxy of personal 48 h exposure. We furthermore studied potential modification of this association by degree of urbanisation.
Method: We first used an initial NISMap estimation (at an assumed height of 4.5 m) for 9563 randomly selected addresses in order to oversample addresses with higher exposure levels and achieve exposure contrast. We included 47 individuals across the range of potential RF-EMF exposure and used NISMap to re-assess downlink exposure at the home address (at bedroom height). We computed several indicators to determine the accuracy of the NISMap model predictions. We compared residential RF-EMF model predictions with personal 48 h, at home, and night-time (0:00–8:00 AM) ExpoM3 measurements, and with EME-SPY 140 spot measurements in the

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http://dx.doi.org/10.1016/j.scitotenv.2016.01.194

Mobile phone base station
Urbanisation

bedroom. We obtained information about urbanisation degree and compared the accuracy of model predictions in high and low urbanised areas.
Results: We found a moderate Spearman correlation between model predictions and personal 48 h ($r_{Sp} = 0.47$), at home ($r_{Sp} = 0.49$), at night ($r_{Sp} = 0.51$) and spot measurements ($r_{Sp} = 0.54$). We found no clear differences between high and low urbanised areas (48 h: high $r_{Sp} = 0.38$, low $r_{Sp} = 0.55$, bedroom spot measurements: high $r_{Sp} = 0.55$, low $r_{Sp} = 0.50$).
Discussion: We achieved a meaningful ranking of personal downlink exposure irrespective of degree of urbanisation, indicating that these models can provide a good proxy of personal exposure in areas with varying build-up.

1. Introduction

There has been a widespread increase in exposure to radiofrequency electromagnetic fields (RF-EMF) in recent decades due to the rise of mobile phone use and developments in communication technology (Andrews and Claussen, 2012; Tomitsch and Dechant, 2015). Potential risks from modern technology can lead to concern within the general public, especially when exposure is perceived as unavoidable and uncontrollable (Slovic, 1987), such as the potential health risk of exposure to RF-EMF from mobile phone base stations (Siegrist et al., 2005). As a result, several studies addressed the possible association between RF-EMF exposure and development of various health problems (e.g. Blettner et al., 2009; Röösli et al., 2010). If such health effects exist, they are likely to be small, and therefore accurate and efficient RF-EMF exposure assessment for large populations is essential for epidemiological studies (Neubauer et al., 2007).

RF-EMF exposure from mobile phone base stations is difficult to assess because of the large 3D spatial variation in exposure patterns and subject movement patterns. Personal measurements are at present not feasible for large epidemiological studies due to time and cost constraints, and therefore models are needed to accurately and efficiently estimate exposure. The geospatial model NISMap (Bürgi et al., 2008, 2010) was developed to efficiently estimate exposure from fixed site transmitters. Validation studies (Beekhuizen et al., 2013, 2014b; Bürgi et al., 2008, 2010) found a reasonably good agreement (Spearman correlations around $r_{sp} = 0.7$) between measured and modelled values for both outdoor and indoor static locations. Epidemiological studies (e.g. Frei et al., 2012) have used these fixed site estimates as exposure assessment with the implicit assumption that they reflect personal exposure levels. However, the agreement between measurements and model predictions at static locations does not account for subject movement patterns, and therefore agreement with personal measurements may be lower.

Studies that compared geospatial model predictions with personal measurements are scarce. A study by Frei et al. (2010) found a poor correlation between model predictions and personal 7 day measurements ($r_{sp} = 0.28$) based on a comparison of model predictions by NISMap of RF-EMF levels from fixed site transmitters (FM, TV, Tetrapol, mobile phone base station downlink (hereafter referred to as downlink)) with personal measurements from all far field RF-EMF exposure sources (including FM, TV, Tetrapol, mobile phone downlink, but also mobile phone uplink (hereafter referred to as uplink), DECT, and W-LAN). Martens et al. (2015) compared downlink predictions by NISMap with downlink personal measurements for a 24-h period and found a slightly higher but still modest Spearman correlation ($r_{sp} = 0.36$). These previous results would indicate that there is considerable misclassification in personal RF-EMF exposure levels when approximated by fixed site estimates. However, these previous studies may have suffered from several methodological limitations. First, the measurement devices used in these studies (EME-SPY 120: Frei et al. (2009), EME-SPY 121 Martens et al. (2015)) were not sensitive enough to detect low field strengths (below 6.63 E-03 mW/m^2), they underestimate actual RF-EMF levels and may suffer from crosstalk between different frequency bands (Bolte et al., 2011; Lauer et al., 2012). Recently, improved measurement devices such as EME-SPY 140 and the ExpoM3 have become available. Secondly, the use of more accurate height and antenna input data can improve the accuracy of NISMap model predictions (Beekhuizen et al., 2014a).

In this study we compare NISMap model predictions with personal 48 h, at home, at night, and static measurements in the bedroom, using more accurate height and antenna input data and contemporary measurement instruments. We will address two factors that could impact exposure assessment in epidemiological studies: (i) variability in areas with different degrees of urbanisation, as different spatial characteristics (build-up topology) in urban versus rural areas may influence the accuracy of the model predictions; and (ii) the relative contribution of downlink RF-EMF exposure to total far field RF-EMF exposure, and whether this contribution is different for high and low exposed subjects.

2. Method

2.1. Population and sampling strategy

The sampling strategy and flow of participants are displayed in Fig. 1. To recruit participants distributed across a broad exposure range, we used NISMap to estimate RF-EMF downlink levels for 9563 randomly selected addresses in five towns near Utrecht, the Netherlands (Bunnik, Odijk, Zeist, de Bilt and Bilthoven). Potential subjects (one per household) were approached through postal mail addressed to their household. These households were selected based on geographical spread, variation in urbanisation degree (information about the urbanisation level at postal code level was obtained from the Dutch CBS (Statistics Netherlands)), and a broad variation in exposure range. Based on initial exposure estimation (see model description and model input) we invited potential subjects equally distributed over three categories: <0.0265 mW/m^2, 0.0265–0.106 mW/m^2 and >0.106 mW/m^2. The thresholds 0.0265 mW/m^2 (0.1 V/m) and 0.106 mW/m^2 (0.2 Vm) corresponded with respectively the top 10% and the top 1% of the distribution of modelled (initial) RF-EMF downlink values. Assumed low exposed subjects (<0.0265 mW/m^2) were sampled from the same neighbourhoods as higher exposed subjects to ensure maximum comparability (e.g. similar type of residences). No more than two households from each street, and no addresses directly next to each other, could participate, so that sufficient geographical spread was achieved, and to avoid correlated errors. Invitation letters were sent in batches of approximately 50 letters each until the desired number of participants was reached. From the 276 invitation letters that were sent, 40 individuals participated, as well as eight spontaneous applicants who were friends or (distant) neighbours from the selected households. All participants signed a written informed consent. Participants were given a 20 euro voucher as an incentive. After completing the first set of measurements, we asked if the participant was willing to take part in a repeated measurement, which 16 participants agreed to. The purpose of these repeated measurements was to assess whether one 48 h measurement period is an adequate period to assess long-term personal exposure. All measurements took place between November 2013 and May 2014.

2.2. Model description and model input

We modelled RF-EMF exposure to different downlink frequencies (UMTS, GSM900, GSM1800) from mobile phone base stations in the

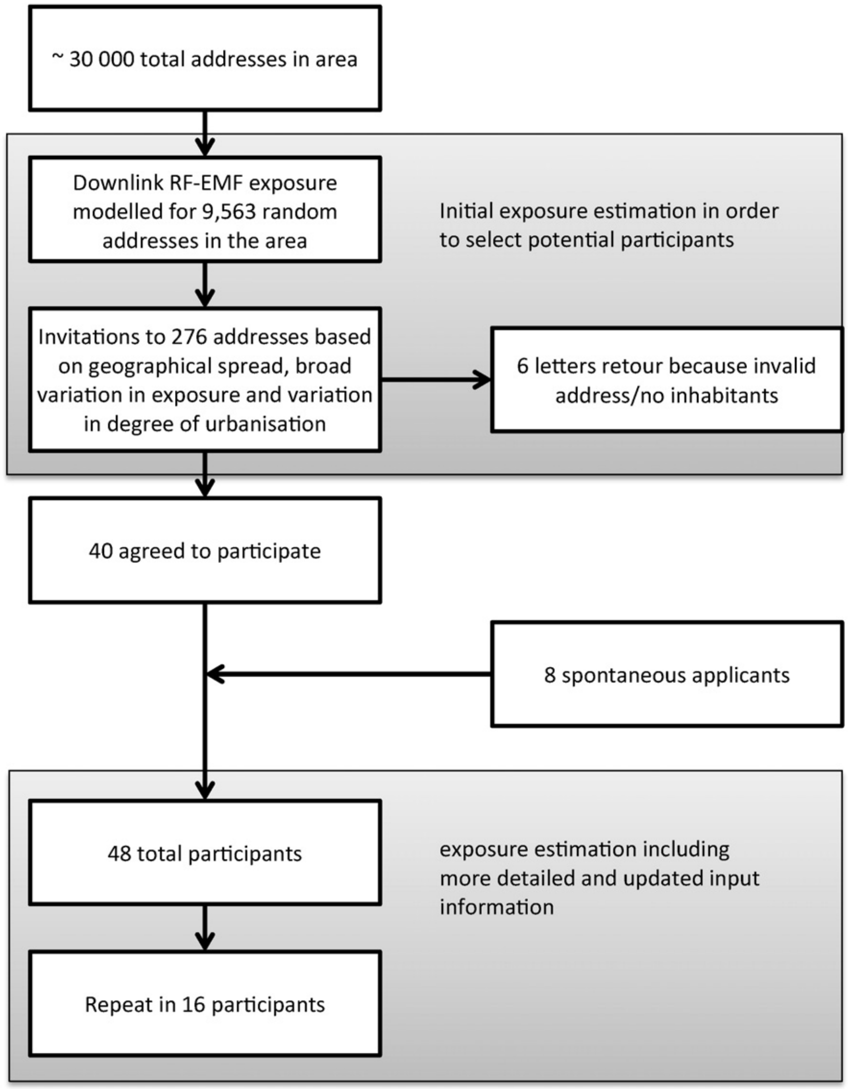

Fig. 1. Participant sampling strategy and flow of participants.

bedroom of the study participants using a three-dimensional radio wave propagation model (NISMap). We first modelled exposure for 9563 random selected households out of an approximate 30,000 households in the study area. This allowed the selection of participants over a broad exposure range. For this initial estimation we had no information on the bedroom height, which in previous uncertainty analyses has been shown to be influential (Beekhuizen et al., 2014a), and had available only an older list of the presence of communication transmitters. Therefore, we remodelled exposure for all participants with more detailed and updated input data. The required input data and technical details of the model have been described in several previous studies (e.g. (Beekhuizen et al., 2015; Bürgi et al., 2008, 2010). Briefly, detailed information on communication transmitters (for initial estimation transmitter data from 2011 and for the final estimation transmitter data from 2013), such as the coordinates, beam direction, and height of the transmitter was obtained from the Dutch Radiocommunications Agency (Agentschap Telecom). The estimated output power of the antennas is based on long-term averages. Coordinates of home addresses were obtained from the Dutch Cadastre in 2012 (BAG, Basisregistraties Adressen en Gebouwen). A 3D representation of all buildings in the Netherlands was constructed 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).

Decrease of RF-EMF levels with distance was calculated using the Double Power Law (ITU, 2009) as previously done by Bürgi et al. (2010) and Beekhuizen et al. (2013, 2014b). Building damping values was set equal to Martens et al. (2015) to correct for the attenuation of radio waves by buildings. Damping of roofs was set to 4.5 dB, damping of walls to 3 dB and the inside damping to 0.6 dB/m for all buildings. The bedroom height was used as input for the model, as people generally spend the majority of their time in their bedroom while they are at home. For the initial model estimation to select participants, the bedroom height input was set at 4.5 m, unless the total building height was lower than 5.0 m. In that case we used the total building height minus 0.5 m. To obtain the bedroom height for the final model estimation, we asked subjects the total number of floors in the building and the floor number of their bedroom (where ground level counts as zero). We used the following formula to calculate approximate bedroom height (Beekhuizen et al., 2014b):

$$\textit{bedroom height} = \frac{\textit{building height in metres}}{\textit{total number of floors}} * \textit{floornumber bedroom} + 1.5 \text{ metres}.$$

2.3. Bedroom measurements

Bedroom spot measurements were performed by the researchers at the home addresses of all study participants using a Satimo EME-SPY 140 exposimeter (the detection limit for the downlink frequencies was $6.63 * 10^{-5}$ mW/m^2 (0.005 V/m) sampling every 4 s (http://www.eudisa.com/fileadmin/PDFs/industrieloesungen/EMESPY140_EN.pdf). The Satimo EME-SPY 140 measures the RF-electric fields in 14 separate frequency bands ranging from FM (88–108 MHz) to WiFi 5G (5150–5850 MHz). This measurement device was chosen for the spot measurements in order to compare the results with our previous studies (Beekhuizen et al., 2014b) as well as for the possibility to immediately read out the data to check if the measurements were successful. The measurement device was placed on a wooden tripod. We measured for 2 min at seven spots in the room starting in the centre of the room at height 1.10, 1.50 and 1.70 m, and in all corners of the room at height 1.50 m with a distance to the centre of approximately 1 m (conducted in the same manner as e.g. Bürgi et al., 2010; Beekhuizen et al., 2014b).

2.4. Personal measurements

To determine personal exposure over a period of 48 consecutive hours, the participants carried a small hip bag containing a radiofrequency metre (ExpoM3, sampling frequency set to every 30 s) for a period of 48 h. The ExpoM3 measures the RF-electric fields in 16 separate frequency bands (ranging from FM Radio (88–108 MHz) to WiFi 5G (5150–5875 MHz). We did not include the LTE uplink and downlink frequencies for calculating total far field RF-EMF exposure (see Table 1 for a list of frequencies), as LTE was not yet introduced in our study area at the time of the measurements. The ExpoM3 measurement device was chosen for personal measurements for its small size and low weight, as well as long battery life since we aimed for a 48 h measurement period. The lower detection limits of the ExpoM3 radiofrequency metre for the downlink frequencies were: UMTS downlink: $2.39 * 10^{-5}$ mW/m^2 or (0.003 V/m), GSM900 downlink: $6.63 * 10^{-5}$ mW/m^2 or (0.005 V/m) and GSM1800 downlink: $6.63 * 10^{-5}$ mW/m^2 (or 0.005 V/m). Participants were asked to continue their daily activities as usual. During sleep, participants were asked to place the cotton bag containing the device on a bedside table at a minimum distance of 30 cm from the wall. We asked participants to keep a diary in which they specified at what times they left and entered their home. The diary was also used to register any time the participant did not carry the bag with the measurement device (for example swimming, sports or forgetting to wear the bag) as well as to register any incidents such as dropping the bag by accident.

2.5. Urbanisation

To get a measure of the degree of urbanisation, we used the address density for each postal code, based on publicly available data from the Central Bureau of Statistics from 2010 (five categories: <500, 501–1000, 1001–1500, 1501–2500 and –>2500 addresses per km^2). We dichotomized this variable due to few observations in some of the categories to two categories: low urbanisation, 0–1500 addresses per km^2; and high urbanisation, >1500 addresses per km^2.

Table 1
Frequency bands from the ExpoM3 used to calculate total far field RF-EMF exposure.

Band name	Frequency range
FM radio	87.5–108 MHz
DVB-T	470–790 MHz
GSM900 uplink	880–915 MHz
GSM900 downlink	925–960 MHz
GSM1800 uplink	1710–1785 MHz
GSM1800 downlink	1805–1880 MHz
DECT	1880–1900 MHz
UMTS uplink	1920–1980 MHz
UMTS downlink	2110–2170 MHz
ISM 2.4 GHz	2400–2485 MHz
WiMax 3.5 GHz	3400–3600 MHz
ISM 5.8 GHz/U-NII 1–2e	5150–5875 MHz

2.6. Data analysis

In a few instances, short time slots of the 48 h measurement periods were removed from the data because the participant reported in the diary not having carried the measurement device for reasons other than night-time (for example because the participant went running outside and it was inconvenient to carry the measurement device). In total, this amounted to 17.5 h summed over six participants, which was less than 1% of the total (2076 h) sampled hours.

Measurements below the detection limit were set at the detection limit (for the EME-SPY spot measurements in the bedroom: 0% of the GSM900 DL, 30% of the GSM1800, and 15% of the UMTS DL. For the ExpoM3, 48 h personal measurements: 2% of the GSM900 DL, 12% of the GSM1800, and 20% of the UMTS).

We computed the total downlink exposure for each subject by summing the mean RF-EMF levels of the GSM 900 downlink, GSM 1800 downlink and UMTS downlink frequencies (in mW/m^2) for the following periods: the overall 48 h period, the time spent at home as reported in the diary, and assumed night-time between 0:00 and 08:00 AM. Of 21 participants the actual night-time (mean duration: 16.4 h, start time: 23:32, and end time: 07:41) was known and we used this data in a sensitivity analysis. Furthermore, we assessed the agreement between the initial and final model estimation to evaluate the method of participant selection. In addition, we evaluated the repeated 48 h sampling scheme for personal measurements by comparing initial and repeated 48 h measurements using the intraclass correlation and Spearman (r_{Sp}) coefficients.

We computed several indicators to determine the accuracy of the NISMap model predictions: mean modelled and measured values, ratio (mean modelled value divided by the mean measured value), mean difference between modelled and measured values (modelled–measured), mean relative difference (mean difference divided by the average of measured and modelled values), precision (standard deviation of differences between modelled and measured values), coefficient of variation (ratio of the standard deviation to the mean) and Spearman rank correlation between modelled and measured values. We compared differences in the association between model predictions and measurements between areas with high and low urbanisation.

We compared the contribution of each frequency to the total far field RF-EMF 48 h exposure for all participants and for participants with downlink exposure on or below the median, above the median. Analyses were carried out using the statistical programme R (3.1.0) and SAS 9.2.

3. Results

3.1. Descriptives

One participant had to be excluded from the analyses due to failure of the ExpoM3. Failure of the ExpoM3 also occurred in two other instances, but in those cases at least one set of measurements (first or repeated measurement set) was successful. Therefore we analysed data for 47 unique participants and 14 repeated measurements resulting in total 61 observations.

Our study population consisted of 26 male subjects and 21 female subjects between the ages of 21 and 80. Less than half of the participants lived in urban areas (N = 21; 45%) while the other participants lived in more rural areas (n = 26; 55%). The mean measured duration with the ExpoM3 for all participants was 43.8 h, including night-time and time spent outside the home and excluding day-time periods not carrying

Table 2
Distribution of modelled and measured values of RF-EMF downlink (mW/m^2) for all 47 participants.

	Min	25% quantile	Median	75% quantile	Max
Modelled	0.000	0.025	0.066	0.141	1.210
Measured 48 h	0.002	0.010	0.027	0.051	1.526
Measured at home	0.001	0.005	0.012	0.050	1.547
Measured at night	0.000	0.004	0.011	0.057	1.829
Spot measurements bedroom	0.000	0.003	0.015	0.098	6.844

the device. On average, participants were at home for 34.2 h (78%). In a sensitivity analysis ($n = 21$) we compared the measurement values for actual reported bedtime and the assumed night-time, and these were similar (reported bedtime: mean 0.151 mW/m^2 (SD 0.402), assumed night-time: mean 0.151 mW/m^2 (SD 0.404). We therefore conducted all analyses using the assumed bedtime allowing the use of the full set of 47 participants.

3.2. Description of initial model estimation

The mean initial exposure for 9563 random addresses in the area estimated by NISMap was 0.010 mW/m^2 (SD 0.024) for all addresses, 0.078 mW/m^2 (SD 0.062) for the 40 participants in the study that were selected based on the initial estimation. The mean final NISMap model estimation for these 40 participants was 0.159 mW/m^2 (SD 0.238), and the correlation between the initial and the final estimation was $r_{Sp} = 0.40$. Including the spontaneous applicants resulted in an average exposure of 0.140 mW/m^2 (SD 0.225).

3.3. Inter- and intra-individual variability in RF-EMF measurements

We assessed the variability for the first and repeat 48 h measurements available for 14 participants. There was more inter-individual (between persons) variation than intra-individual (between the first and repeat sets of measurements) variation, as reflected in a high intraclass correlation (0.81) and Spearman correlation ($r_{Sp} = 0.76$). Subsequent analyses are therefore based on the first successful 48 h measurement period of all participants.

3.4. Accuracy of the model predictions

Table 2 shows the distribution of modelled and measured 48 h downlink RF-EMF values for all 47 participants. Table 3 shows the accuracy of the model predictions for the first measurement of all 47 participants. The mean modelled value for the 48 h overall period was 0.140 mW/m^2, the mean measured value was 0.091 mW/m^2. The mean measured value from the spot measurements in the bedroom was 0.292 mW/m^2. We found a Spearman correlation of $r_{Sp} = 0.47$ between modelled and measured values for the 48 h overall period, and $r_{Sp} = 0.54$ between model predictions and spot measurements in the bedroom. In Fig. 2 we show two Bland–Altman plots (Bland and Altman, 1986) for the absolute (Fig. 2A) and the relative differences (Fig. 2B) between the NISMap model predictions and the 48 h personal measurements. We more often observe overestimation than underestimation of RF-EMF, and the degree of overestimation increases for higher absolute values, but not for relative values. There are no consistent differences in relative prediction accuracy (Fig. 2, Table 4 (r_{Sp})) for addresses in high versus low urbanised areas. However, measured values are higher in low urbanised areas, while modelled values are similar in high and low urbanised areas, resulting in different modelled/measured ratios.

3.5. Downlink contribution to total far field RF-EMF

On average, downlink exposure contributed for 64% to total far field RF-EMF exposure for the 48 h period. When the contribution is assessed separately for subjects with a downlink exposure below and above median, we find that downlink contributed respectively 18% and 76% to the total far field RF-EMF exposure.

4. Discussion

4.1. Interpretation of findings

In this study we expanded on previous studies to assess the validity of using NISMap model predictions at the home address as a proxy for personal downlink RF-EMF exposure from mobile phone base stations in epidemiological studies. Compared to previous studies (Bürgi et al., 2010; Martens et al., 2015), we included more high exposed subjects and used improved model input data, as well as contemporary measurement devices. Our results showed that participants can be meaningfully ranked by modelled exposure at the home address irrespective of the degree of urbanisation, and that RF-EMF from mobile phone base stations can be a major source of total RF-EMF exposure for a portion of the population with high downlink exposure.

A similar measurement study with data from 2009/2010 reported a Spearman correlation of $r_{Sp} = 0.36$ between model predictions and 24 h personal measurements (Martens et al., 2015). The current study indicated better agreement ($r_{Sp} = 0.47$) between model predictions and personal measurements, possible owing to improved measurement devices (EME-SPY 140 vs. EME-SPY 120) and better model input data, mainly improved height estimation, and improved transmitter data. Beekhuizen et al. (2014b) collected spot measurements in the bedroom for 30 households and found a Spearman correlation of $r_{Sp} = 0.60$ with model predictions using NISMap. In our study, we found a similar value ($r_{Sp} = 0.54$). Since the spot measurements in the bedroom corresponded most closely with the modelled location by NISMap, we expected better agreement between these spot measurements and the model predictions than with personal 48 h measurements. The difference in correlation between 'spot measurements–model prediction' and 'personal 48 h measurement–model prediction' can be interpreted as the loss in prediction accuracy due to personal movement patterns. In our study, the loss in accuracy (0.54–0.47) seems minimal. The extent of

Table 3
Comparison of downlink RF-EMF (mW/m^2) model predictions with personal 48 h, time spent at home, and at night measurements, and with spot measurements in the bedroom.

	Personal 48 h (ExpoM3)	At home (ExpoM3)	At night 0:00–08:00 (ExpoM3)	Spot measurements bedroom (EME-SPY 140)
Mean measured	0.091	0.083	0.090	0.292
Mean modelled	0.140	0.140	0.140	0.140
Ratio modelled/measured	1.532	1.691	1.557	0.478
Mean difference (modelled–measured)	0.048	0.057	0.050	−0.152
Mean relative difference	0.30	0.60	0.61	0.41
Precision	0.17	0.17	0.20	0.82
Coefficient of variation	2.60	2.90	3.01	3.66
r_{Sp} correlation between measured and modelled	0.47	0.49	0.51	0.54

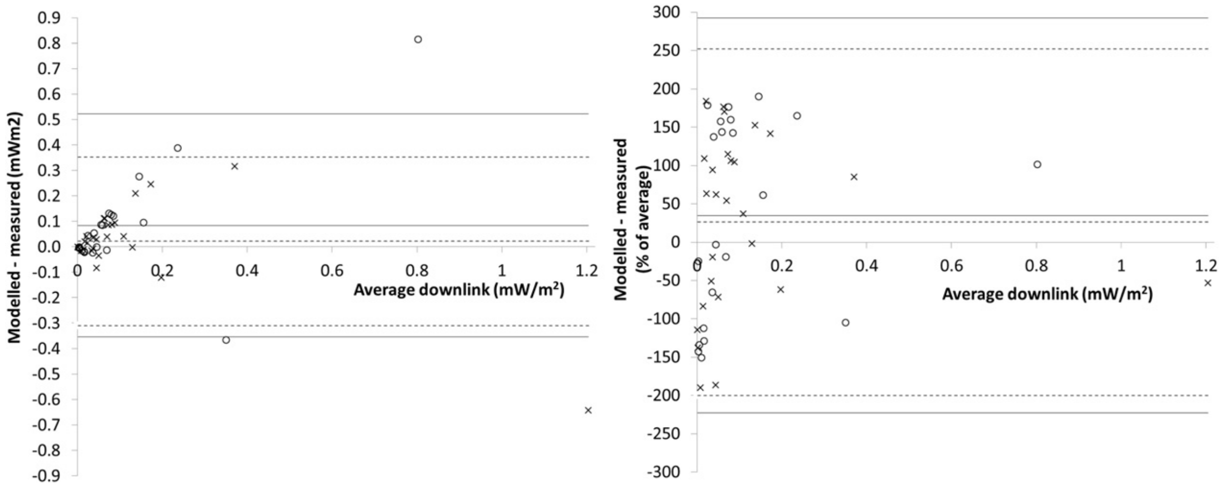

Fig. 2. Bland–Altman plot of the mean downlink RF-EMF, showing the absolute (A. left) and relative (B. right) differences between model predictions and measured values for the 48 h period. An 'x' represents an address in an area with low urbanisation (≤1500 addresses per km^2), and an 'O' an address in an area with high urbanisation >1500 addresses per km^2). The horizontal lines (solid = x, striped = O) represent the mean, the mean +2 standard deviations, and the mean −2 standard deviations.

the loss in prediction accuracy is influenced by the amount of time participants spend at home/in the bedroom, and by activities/locations. Our study population spent somewhat more time at home (78%) than in other environmental studies (65–70%, e.g. Brasche and Bischof, 2005; Martens et al., 2015), which may have resulted in a slightly optimistic estimate of the loss in prediction accuracy.

We were especially interested in knowing if the prediction accuracy differed by urbanity degree. If this would be the case, this could bias exposure estimations and as a consequence, might bias epidemiological exposure-response analyses especially if the health effect of interest is also associated with level of urbanisation. Earlier validation studies by Beekhuizen et al. (2014b) focused on highly urbanised areas, with more complicated spatial characteristics and potentially less accurate model estimation than in low urbanised areas. Our results did not indicate clear differences in correlation (Fig. 2, Table 4). However, the modelled/measured ratios were lower in less urbanised areas, and urbanisation degree should remain a point of attention in exposure assessment.

Previous studies reported that the contribution of RF-EMF exposure from mobile phone base stations to total far field RF-EMF exposure differs across countries and activities but is generally low (Bolte and Eikelboom, 2012; Joseph et al., 2010). Neubauer et al. (2007) did not recommend epidemiological studies on RF-EMF exposure to mobile phone base stations alone, due to uncertainty in exposure assessment and low contribution to overall RF-EMF exposure in general. Our results show that this contribution differs depending on the level of exposure to RF-EMF from mobile phone base stations. For participants in our study with exposure from mobile phone base stations above the median, the contribution to total far field RF-EMF exposure was 76%, compared to 18% for participants with lower exposure.

4.2. Strengths and limitations

Strengths of this study were the accurate input data for the NISMap model predictions and the contemporary measurement devices used to measure RF-EMF fields. In contrast to previous studies (Beekhuizen et al., 2014b; Frei et al., 2010; Martens et al., 2015), we did not focus on spot measurements or on personal measurements, but did both type of measurements, enabling us to evaluate the impact of personal movement patterns on prediction accuracy. Previous RF-EMF personal measurement studies differed in the length of the measurement period (Frei et al. (2009): 1 week, Martens et al. (2015): 24 h). Large temporal variation in personal exposure patterns could mean that longer measurement periods or repeated measurements would be necessary to get an indication of the typical long-term exposure of an individual. We found a high intraclass correlation (0.81) between repeated measurements, indicating that one measurement period of 48 h is adequate to assess long-term personal exposure.

A limitation of this study arose from using different measurement devices for spot measurements in the bedroom (EME-SPY 140) and personal measurements (ExpoM3), which may have influenced the comparison between spot measurements and personal measurements. The ratio of modelled to measured values was different for the measurements with the ExpoM3 and the EME-SPY 140 device. However, limited side-by-side testing of the two devices (results not presented) showed no consistent differences between values of the two measurement

Table 4
Mean RF-EMF downlink exposure (mW/m^2) and Spearman correlations with modelled exposure by urbanisation[a].

	High urbanity (n = 21)			Low urbanity (n = 26)		
	Mean	r_{sp}	Ratio modelled/measured	Mean	r_{sp}	Ratio modelled/measured
Modelled	0.152			0.130		
Measured						
48 h period	0.068	0.38	2.22	0.110	0.55	1.18
At home	0.069	0.52	2.21	0.094	0.46	1.38
At night	0.060	0.46	2.52	0.113	0.59	1.14
Spot measurements in bedroom	0.168	0.55	0.91	0.393	0.50	0.33

[a] High urbanisation: >1500 addresses per km^2, low urbanisation: ≤1500 addresses per km^2.

devices and all measurement devices were calibrated both before and after the measurement period. Like model predictions, measurements have their own limitations, and are not a perfect 'golden standard' (Bolte et al., 2011; Lauer et al., 2012). Another limitation of this study was the lack of information regarding mobile and DECT phone use. Gaining information about phone use would require more detailed activity diaries, which can be bothersome for participants and lead to selective dropout. Phone use is a source of near field RF-EMF exposure (the uplink and DECT frequencies), for which there can be large differences in measurement values depending on small differences in distance. Measurement devices such as the ExpoM3 can therefore not give a reliable indication of full-body near field exposure, and the measurement values in the uplink bands of our measurement values (data not presented here) are a mix of both near field exposure (own phone use) and far field exposure (phone use by other people in the area). Therefore and given our study aim, we focused on downlink frequencies.

We oversampled high exposed subjects to obtain subjects across a broad range of exposure, using an initial model estimation with incomplete input data (less accurate height input and transmitter data). A disadvantage of this selection method is that the results of this study are not representative for the general population. We selected all participants from the same neighbourhoods as participants living at addresses with a high exposure estimate based on the initial estimation. As a consequence, we have selected neighbourhoods with high exposure contrasts, which may reflect spatial characteristics of these neighbourhoods such as large variation in building heights. Since estimation of exposure with a 3D geospatial model may be more difficult in such areas than in areas with less spatial variation, we may have slightly underestimated the ability of NISMap to classify subjects as high or low exposed.

4.3. Conclusion

Findings of previous measurement studies suggested that the agreement between model estimations of downlink RF-EMF from mobile phone base stations at the home address and personal measurements was substantially lower than the agreement with measurements at a static location. In our study, we found that the loss in prediction accuracy resulting from movement patterns and specifically, the time spent at locations other than the home address, is limited. Although misclassification is present, it is possible to meaningfully rank participants on modelled downlink exposure and to identify relatively high exposed individuals, both for low and high degree of urbanisation. The contribution of exposure from mobile phone base stations to total far field RF-EMF exposure can be substantial for subjects with a high exposure. Large epidemiological studies regarding health effects of RF-EMF from mobile phone base stations are now feasible, as limited individual input data is required owing to the availability of an adequate prediction model.

Disclosure

The authors declare no conflicts of interest.

Acknowledgements

This research was supported by the ZonMW grants 85200001, from the Dutch programme on Electromagnetic Fields and Health Research, the Netherlands. We would like to thank Lutzen Portengen for processing the measurement data into organised datasets, Anke Huss for advice on the measurement protocols, and Annemarie Melis for assisting with the measurements. We would also like to thank all the participants for taking the time and effort to participate in our study.

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