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

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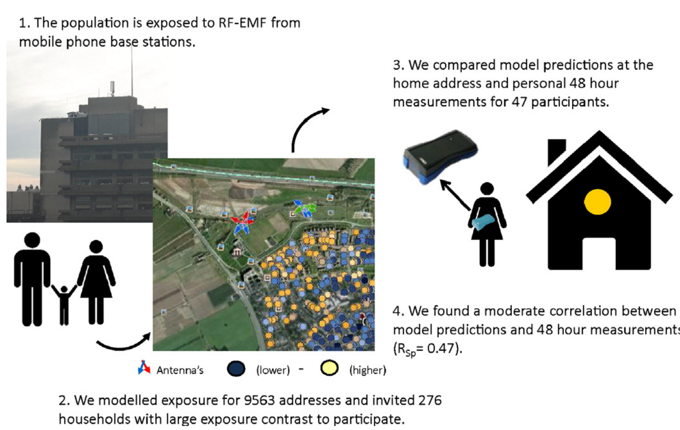
HIGHLIGHTS

- 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



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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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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