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Applying indoor and outdoor modeling techniques to estimate individual exposure to PM2.5 from personal GPS profiles and diaries: A pilot study

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ABSTRACT

Impacts of individual behavior on personal exposure to particulate matter (PM) and the associated individual health effects are still not well understood. As outdoor PM concentrations exhibit highly temporal and spatial variations, personal PM exposure depends strongly on individual trajectories and activities. Furthermore, indoor environments deserve special attention due to the large fraction of the day people spend indoors. The indoor PM concentration in turn depends on infiltrated outdoor PM and indoor particle sources, partially caused by the activities of people indoor.

We present an approach to estimate PM2.5 exposure levels for individuals based upon existing data sources and models. For this pilot study, six persons kept 24-hour diaries and GPS tracks for at least one working day and one weekend day, providing their daily activity profiles and the associated geographical locations. The survey took place in the city of Münster, Germany in the winter period between October 2006 and January 2007. Environmental PM2.5 exposure was estimated by using two different models for outdoor and indoor concentrations, respectively. For the outdoor distribution, a dispersion model was used and extended by actual ambient fixed site measurements. Indoor concentrations were modeled using a simple mass balance model with the estimated outdoor concentration fraction infiltrated and indoor activities estimated from the diaries. A limited number of three 24-hour indoor measurements series for PM were performed to test the model performance.

The resulting average daily exposure of the 14 collected profiles ranged from 21 to 198 µg m^{-3} and showed a high variability over the day as affected by personal behavior. Due to the large contribution of indoor particle sources, the mean 24-hour exposure was in most cases higher than the daily means of the respective outdoor fixed site monitors.

This feasibility study is a first step towards a more comprehensive modeling approach for personal exposure, and therefore restricted to limited data resources. In future, this model framework not only could be of use for epidemiological research, but also of public interest. Any individual operating a GPS capable device may become able to obtain an estimate of its personal exposure along its trajectory in time and space. This could provide individuals a new insight into the influence of personal habits on their exposure to air pollution and may result in adaptation of personal behavior to minimize risks.

KEYWORDS

Personal exposure, PM2.5, GPS, activity profiles, GIS, PM model

1 INTRODUCTION

Airborne particulate matter (PM) is in the focus of public interest since ambient PM2.5 (fine particles, diameters < 2.5 µm) concentrations have been significantly related to health effects by epidemiological studies (Dockery et al., 1993; Pope et al., 2002). In the European Union rigid regulations exist for maximum concentrations of PM10, which is the inhalable PM fraction with diameters below 10 µm (EC, 1999). The national environmental agencies operate networks of fixed measurement stations to control compliances with the thresholds. Due to the low correlations between ambient fixed site measurements and personal exposure of individual persons, fixed monitors, such as routine stations of air quality networks, alone cannot provide good estimates of individual particle exposure (Singh and Sioutas, 2004; Özkaynak et al., 2008). Thus, linking health effects and ambient concentrations likely underestimates the amount of health burdens caused by air pollution (Jerrett et al., 2005a). Developing methods to estimate individual exposure is therefore an essential part of risk assessment in public health, to enable a direct link from personal exposure levels to the associated individual health effects.

The amount of personal exposure to PM has been examined in several surveys, e.g., during the Particle Total Exposure Assessment Methodology (PTEAM, Özkaynak et al., 1996a) in the USA, and EXPOLIS (Jantunen et al., 1998; Hänninen et al., 2004a) in Europe. Results show that personal exposures of individuals to PM10 and partially to PM2.5 are higher than the respective indoor and outdoor environmental concentrations (Toivola et al., 2004; Ferro et al., 2004). It is important to notice that this effect, called “personal cloud”, is still a subject under research and cannot be included in microenvironmental models so far. However, in the case of particulate matter, the direct measurement of personal exposure seems infeasible for larger cohorts over a long-time period due to logistic limitations. Furthermore, cumulative measurements of PM exposure over a relatively long time period yields no specific information about the sources, locations, and activity that contributed to the measured exposure. Hence, individual behavior cannot easily be associated with high or low PM exposure.

A number of models for assessing personal exposure, such as SHEDS-PM (Burke et al. 2001) and HAPEM (Özkaynak et al. 2008), exist. They are based on the so-called indirect model approach (Moschandreas and Saksena, 2002). This approach combines the time spent at visited microenvironments and activities of individual persons, as taken from diaries in epidemiological studies, e.g., the National Human Activity Pattern Survey (NHAPS, Klepeis et al., 2001), and the estimated PM concentrations at every microenvironment. These kinds of indirect models usually use estimates of mean concentrations in microenvironments, as a combination of infiltrated outdoor air and indoor source emissions, without taking the outdoor spatial distribution on an urban scale, and influences through individual trajectories, into account. Zidek et al. (2005) for example present pCNEM, a stochastic model for estimating personal exposure from large activity surveys like NHAPS. They address the location in a coarse approach by distinguishing between home and workplace and identifying the districts that are associated to the nearest pollution monitor sites. This model enables the estimation of the personal exposure for randomly picked individuals by running the stochastic model several times on similar diaries of the same population subgroup. However, the aim of their model is to give probabilistic estimates for certain population subgroups instead of modeling time and space variant exposure dynamics of a specific individual person that we are aiming for.

All these models are not including the exact geographical position of the individuals or the spatio-temporal urban scale distribution of particle concentration. Hertel et al. (2008) found that even the choice of route while commuting, can influence the amount of exposure for individuals. The high intra-urban variability demands spatially referenced exposure models. With the upcoming trend of mobile devices such as cell phones that can be used as a GPS receiver, new possibilities for the collection of large numbers of geographically referenced human motion profiles are available. The GPS coordinates provide information about the outdoor location of individual persons throughout the day with an accuracy of a few meters. By combining an outdoor dispersion model with actual fixed outdoor measurements, we tried to estimate the spatial distribution of PM for the investigation area during the measurement intervals. Combining this modeled outdoor PM concentration with different building environments, indoor sources and simple particle dynamic factors such as deposition and air exchange, yield estimated time series of indoor particle concentrations. Geographical Information Systems (GIS) offer a large and powerful environment to develop and run such models by building on the existing spatial analysis functionality.

The aim of this paper is the development of methods for estimating personal PM2.5 exposure to avoid the expensive and laborious direct measurements. We assume that combining the estimated spatial distribution outdoors with indoor modeling techniques and GPS positions of the individuals gives a more detailed picture of the personal exposure dynamics than the common indirect approaches. Anyway, it should be noted that this pilot study was not aimed to provide a new and entirely developed personal exposure model but rather to show and assess a new way of combining existing models for exposure estimation. Building on this basis, these methods could be used not only to sample large cohorts for epidemiological surveys, but also for individuals as an information source about their own personal exposure and health risks. This could lead to the adaptation of personal behavior to avoid high exposure situations. The main objectives of this study are therefore:

i) Development and implementation of an initial GIS based model framework for personal PM2.5 exposure for a case study application. This includes

> a) Adapting an indoor mass balance model and evaluating model performance by conducting a limited number of indoor measurements
>
> b) Estimating the spatio-temporal outdoor PM2.5 distribution with available model approaches and measurement networks

ii) Exploring the potential and limitations of this model approach and identifying future strategies for improvement and application

2 METHODOLOGY & MODEL FRAMEWORK

To estimate personal exposure to PM2.5 we need information about the locations visited by the individuals, the PM2.5 concentrations at each of these locations and the activities influencing these concentrations. In our model framework presented in fig. 1, the test person tracking results are used as input data for the indoor and outdoor concentrations models, respectively. These models, and the processing steps shown in fig. 1, are specified in the following three sections.

The complete model was embedded and implemented as an application in ArcGIS 9.3 from the Environmental Systems Research Institute (ESRI). The GIS environment provides the spatial analysis functions used in the outdoor model coupled to the indoor model. This framework enables the automated processing of activity and motion data of an arbitrary number of test persons. Access to the data sources like the ambient measurement network used for the modelling step is realized via database interfaces. The whole application process is controlled by a graphical user interface (GUI), where the particular test person could be selected. Resulting PM exposure profiles have a spatial resolution of 250 m (due to the outdoor model) and a temporal resolution of 5 minutes (due to the diary precision).

2.1 Test person tracking

During the initial test phase in the winter period between October 2006 and January 2007, six test persons were tracked with a Trackstick™ that saves the persons WGS84 longitude and latitude coordinates every 5 seconds. All test persons live in the city of Münster, NW Germany, where the study took place. The GPS records served as major input for the outdoor model (fig. 1, left side), providing location s_0 of the person at time t_0. For each of these points the actual concentration $C_{out}(s_0,t_0)$ was estimated. Each test person recorded at least two profiles, one on a working day and one on a weekend day.

The diaries were filled by each person him- or herself, detailing their activities with location (microenvironment), start and end time, type of activity, and number of smokers in the room together with the test person. Tab. 1 shows an example diary of a male non-smoking pupil, age 19 years. The recorded activities, such as smoking, cooking, or candle burning, served as input parameters for the indoor particle sources in the indoor model (see fig. 1, Indoor model). Having test persons keep their own diaries involves a simplification of the process, but yields a varying degree of precision, e.g., large, potentially heterogeneous time periods may be followed by detailed differentiation in 5 min resolution.

Each test person also filled out a general questionnaire about residence type, smoking habits, air conditioning habits, heating type, and further personal data. This information helped to identify the parameters that were applied for the indoor model (fig. 1, right side).

2.2 Outdoor model

Our pilot study took place in Münster, a quarter-million inhabitants city in Germany. The North Rhine-Westphalia State Agency for Nature, Environment and Consumer Protection (LANUV) operated three (during the study period temporarily four) ambient fixed site monitors in Münster to control compliance with the thresholds of the European guideline 1999/30/EC. For each station, 30-min means of continuous PM10 measurements with a Tapered Element Oscillating Microbalance (TEOM) were available. To estimate the PM2.5 concentration from these measurements, a scaling factor was applied. The monitors were classified into two (temporarily three) urban traffic stations, located near heavily used main streets with daily motor vehicle numbers between 26k and 30k, and one urban background station located inside a residential area, at least 200 m away from higher traffic regions. Their diurnal concentration cycles show significant differences depending on their positions relative to high traffic regions.

To approximate the spatial distribution of outdoor PM, the particle transport model LASAT, a LAgrange Simulation of Aerosol Transport (Janicke, 1983), was applied for the urban area of Münster. The model takes transport by yearly averaged wind speed and direction, dispersion, sedimentation, dry and wet deposition, and first-order chemical conversion of particulate matter, into account. Input point and line emission sources were annual statistics of street-bound traffic (fig. 2, left side), off-road traffic, rail-bound transport, shipping traffic, industry and residential heating facilities. The model calculation yields average annual PM10 concentrations on a 16 km × 19 km grid with 250 m × 250 m cell resolution. (fig. 2, right side).

By combining the high spatial resolution of the LASAT results with the high temporal resolution of the fixed site monitors, we estimated the PM2.5 concentrations for any GPS location and respective time of all test persons. At location (i.e., GPS coordinate) s_0 the PM2.5 concentration at time t_0 was estimated by:

$$C_{out}(s_0,t_0) = \phi C_{\mathrm{mod}}(s_0) + \phi \frac{1}{k}\sum_{i=1}^{k}(C_{out}(s_i,t_0) - C_{\mathrm{mod}}(s_i)) \qquad (1)$$

where $C_{mod}(s_0)$ is the average model output at location s_0, i = 1, 2, 3, 4 denotes the fixed site monitors, k is the number of monitors taken into account ($k \leq 4$), and ϕ is a scaling factor for PM2.5. The second term on the right side of eq.(1) averages the deviation of the monitor measurements at time t_0 from the yearly model output for the k stations. This deviation is assumed to be the same for every location s_0 at time t_0. As this assumption is realistic only for similar environments and situations, it has to be applied cautiously. For each location s_0, the respective type of measurement station, traffic or background, was used in eq. (1). Therefore, the vicinity of the test person location to streets was taken into account. If the test person's position was within 50 m distance to a major street with more than 10k cars/day, or within 100 m distance to freeways with more than 40k cars/day, all traffic stations in Münster were averaged for the application of eq. (1). Through this algorithm, the diurnal cycle of traffic dynamics was reflected in the model data. In all other cases, data of the background station was applied instead. If, due to measurement failures, no valid concentration for the background station was available, the station with the lowest traffic influence classification was applied. Because the fixed site monitors and the LASAT model provided only PM10 concentrations, we had to use a scale factor ϕ to estimate the PM2.5 concentrations. This was set to 0.6 near busy roads and 0.7 otherwise (Gehrig and Buchmann, 2003; WHO, 2005). The magnitude of the scaling factor is associated with a maximum uncertainty of 0.1. The selected values represent best estimates (see Querol et al., 2004). Which value had to be used, was tested for each position by the vicinity factor described above.

The modeled $C_{out}(s_0,t_0)$ concentration is an estimate of the actual exposure for periods when the test person is outside. For the exposure profile, the concentrations of the GPS position were summarized to 5-minute-intervals. During an indoor environment stop, the last recorded GPS position was used to estimate the associated outdoor concentrations as input for the indoor model (fig. 1).

2.3 Indoor model

As most people spend around 90 % of the day in indoor environments (Klepeis et al. 2001), indoor PM concentration levels have an important impact on personal exposure. To estimate the indoor concentrations, using given knowledge of location and activity log, an indoor model could be used from Koutrakis et al. (1992):

$$C_{in} = \frac{C_{out}\, p\alpha + \frac{\sum_{i=1}^{n} E_i}{V}}{\alpha + D} \qquad (2)$$

where C_{in} is the indoor particle concentration in µg m^{-3}, C_{out} [µg m^{-3}] is the outdoor particle concentration, α [h^{-1}] is the air exchange rate, p is a dimensionless penetration efficiency factor, E_i [µg h^{-1}] is the emission rate for the *i-th* of *n* indoor particle sources, V [m³] represents the room volume, and D [h^{-1}] the particle deposition factor. This type of mass balance model builds on the assumption of a well-mixed single room compartment, steady-state conditions indoors, and is commonly used in published studies on indoor environments and individual exposure (Hoek et al., 2008; Hänninen et al., 2004b; Ferro et al., 2004; Nazaroff, 2004). This assumption is somewhat unrealistic but reasonable for the indirect exposure modeling approach, because the diaries cannot provide detailed information about the room structure and activities in other rooms. Thus, a more complex model would not improve the accuracy of the results as long as the necessary input data is missing.

As mentioned, eq. (2) is true for steady-state conditions and does not account for the influence of previous events such as the aftermath of indoor particle production some time before. The steady-state equation is necessary for estimating the concentration of the initial time step t_0. For each following time step, the concentration difference ΔC_{in} for Δt could be calculated using the dynamic model equation (see also fig. 1):

$$\frac{\Delta C_{in}}{\Delta t} = C_{out,t}\, p\alpha + \frac{\sum_{i=1}^{n} E_{i,t}}{V} - C_{in,t}(\alpha + D) \qquad (3)$$

The parameters of these models depend on physical attributes of the building, furniture in the room, human activity inducing indoor sources and the temperature difference between indoor and outdoor. For estimation of distributions for the parameters in our study area, long-term measurements are necessary. Also many different microenvironments and variations of day/night situations, seasons, and different types of air conditioning, have to be characterized. This is clearly beyond the scope of our study. Instead, we decided to use existing data sets of the physical parameters p, α, E and D from larger surveys, such as EXPOLIS or PTEAM, and adjust and test them with our own 24-hour measurements taken in selected indoor environments. The used parameters for the 10 different microenvironment types that were generalized from the locations described in the diaries are shown in tab. 2 and the additional source strengths in tab. 3. For most of the environments, we applied the mean parameter values from the US PTEAM study (Özkaynak et al., 1996b) because they performed a large set of measurements and reported significant differences in the air exchange rates between daytime (with activities of humans) and night. For temporal or continuous ventilation by opening windows an air exchange of 1.5 h^{-1} (Murray and Burmaster, 1995) was assumed. The volumes V for the environments were taken from the measurement locations and national statistics. Because no values for a pub or restaurant were available from the PTEAM study, we applied the median values of measurements from a study in Bavaria, Germany (Bolte et al., 2008). For the car environment Gulliver and Briggs (2003) found the PM2.5 concentration to be more or less the same, whereas a new survey (Gulliver and Briggs, 2007) showed a ratio of 0.73 between in-car and outdoor concentration. Thus, as this area is still under research, we decided to assume the in-car PM2.5 concentration being the same as outside. For buses and public trains, a value 70 % higher than outside was used, according to the results of a 2-year survey in Munich (Praml and Schierl, 2000).

For validation of the indoor model performance using these parameters in combination with the outdoor model, three indoor measurements in an office, a seminar room, and a residence environment were performed in Münster. The office and the seminar room were located in the same, approximately 30 years old, three-storied, university building on the third upper floor and ground floor, respectively. The residence measurement was performed in a chamber of a four-room flat of 100 m² size in the first floor of a three-storied, 15 years old apartment house in the suburban region of Münster. Both buildings had no air conditioning or any mechanical ventilation installed. For the particle concentration measurements, a 12-stage Electrical Low Pressure Impactor (ELPI, Dekati Ltd., Keskinen et al., 1992) with a measurement range from 0.03 to 10 µm of aerodynamic particle diameter was employed for 24 hours in each of the three environments. The mean particle mass concentration [µg m^{-3}] for 10 min interval was derived from the measurements, assuming a mean particle density of 1.3 g cm^{-3}. The sum of the 9 lower stages yields the PM2.5 mass concentration. To allow comparison with the model results of the consolidated indoor and outdoor model, ELPI measurements were aggregated to 30 min values.

The source strength could be recalculated, if an adaptation is necessary, using the penetration factor, air exchange and deposition rate values and (Koutrakis et al., 1992):

$$\sum_{i=1}^{n} E_i = (C_{in} - R_{I/O} C_{out})\,(\alpha + D)\,V \quad (4)$$

where $R_{I/O}$ is the indoor/outdoor ratio for time periods without emissions from indoor particle sources E_i, i.e., in the absence of people. These calculations were performed with the statistical software R (Ihaka and Gentleman, 1996).

3 Results

3.1 Indoor measurements

The comparisons between the measured indoor PM2.5 concentration in 10 min resolution and outdoor routine station measurements, scaled to PM2.5 in 30 min resolution, are presented in fig. 3. The associated Spearman's rank correlation coefficients are shown in tab. 4.

For the seminar room measurement, periods of human activity especially at the beginning and the end of each seminar are clearly identifiable by higher particle mass concentrations. Generally, the concentration in the seminar room follows the trend of the outdoor measurements which is consistent with the high correlation factors in tab. 4.

In the office, the activity of persons influences the measured PM2.5 values as well, leading to higher concentrations and variability. Especially the candles in the office showed an extreme effect, increasing the indoor PM2.5 concentration by a factor of four. The measured concentration is rather invariant compared to the outdoor values, indicating a weak dependence of the indoor concentration on the outdoor concentration. The considerably low variation in the PM2.5 concentration of the office at night could be explained in theory by a very small air exchange rate due to missing human activity. It should be noted here that the seminar room and the office are in the same university building, leading to the assumption that similar building factors affect the air exchange. However, the results of the two measurements show that there are more factors influencing the air exchange than simply the building type.

During the residence measurement, the indoor concentration was most of the time higher than the outdoor concentrations with an average indoor/outdoor ratio > 2, which is a major difference to the two previous measurements. Also the Spearman’s correlation coefficients are very low (tab. 4). Cooking and smoking within the apartment showed extreme effects on the indoor concentration with different source strengths. The circumstances at night are remarkable, as the PM2.5 concentration in the room increased while the outdoor concentration decreased. A more detailed analysis of the ELPI size spectrum showed that the concentration of particles with diameters < 0.27 µm and those > 2.73 µm decreased, while the middle fraction increased.

3.2 Indoor model performance

In fig. 4 the 30 min averages of the measured indoor concentrations are compared to the modeled values using our model approach with the parameters from tab. 2 and 3. Obviously, the seminar room concentration is well approximated, except for the last seminar. This time period is probably not represented correctly by the model as the door of the seminar room was left wide open after the last seminar and the university building got increasingly busy with students walking through the hallways. Generally, the concentration is slightly underestimated.

The model approximation in the office is not as good as in the seminar room. Because of the lack of source strength data for candles, only the time periods without candle burning were modeled, yielding a clear overestimation of concentrations for all time steps. As this overestimation of the concentration in the office was substantial, we applied eq. (4) with the PTEAM parameters to achieve a more realistic estimate of the indoor particle source strength. The resulting average source strength is 0.368 µg h^{-1} and was updated in tab. 2 for the test persons exposure modeling part.

For the residence environment, the model sometimes under- and sometimes overestimated the PM2.5 concentration. Generally, the first third of the time, the model seems to fit well, whereas the concentrations of the smoking period and its aftermath are overestimated. Finally, the sleeping period concentration towards the end is underestimated by the indoor model.

3.3 Modeled personal exposure profiles

With the estimated parameters and activity profiles used in the model framework (fig. 1), detailed exposure profiles were calculated. Tab. 5 shows the demographic data and exposure mean and standard deviation for all test persons. Two profile examples of test persons 2 and 4 are shown with the associated ambient station measurements in fig. 5 (fig. 5b shows the exposure profile associated to the diary listed in tab. 1). In fig. 6, the mean concentrations of the 24-hour profiles for all six test persons are visualized as a sum of outdoor and indoor source contributions and compared to the mean background station measurements. The only smoker in the survey (test person 2) recorded four instead of two daily profiles. Note that the model results only show the exposure due to passive smoking as for our estimated results it makes no difference whether the test person is an active smoker or another person in the room smokes.

Fig. 5 shows that personal exposure towards PM2.5 is strongly influenced by smoking, cooking, and the outdoor PM concentration. For smokers, an intensity of one cigarette per hour was assumed. The resulting profiles show a repeated rise and fall of the PM2.5 concentration during the smoking periods as caused by the dynamic indoor modeling. Besides smoking and cooking, the visits of pub and restaurant environments are significant contributors to the personal exposure (fig. 5b). During the sleeping phase, the accumulation of particles, which was also observable in the residence measurement results, could be found in the model results, the intensity depending on the ventilation habits of the test persons at night.

Compared to outdoor measurements, the calculated means of the profiles in fig. 6 show mostly a higher personal exposure, which is similar to the conclusions summarized in the EPA (1994) report and found within EXPOLIS (Toivola et al., 2004; Koistinen et al., 2001). The variance of nearly all profiles is very high (tab. 5) except for the weekend of T3 and the working day of T4. These two profiles also show the smallest indoor source contribution in fig. 6. The working day profile of test person 4 is the only one with an average daily exposure lower than the outdoor concentration whereas the weekend profile of T3 is the sole exception with a higher outdoor source contribution than the ambient background mean, indicating a large traffic contribution. All other personal exposure profile means exceeded the outdoor measurement concentration. The profiles (2) of T2 exhibit the highest exposures, and also show the largest variation due to their short term but large indoor contribution, i.e., smoking and cooking. Also the high concentrations assumed for pub and restaurant visits contribute significantly to the personal exposure of some individuals. This can lead to higher concentrations of the weekend profile compared to the working day profile for test persons of certain subgroups. Another factor affecting the personal exposure is the time spent outdoors. Depending on the route individuals take while traveling through the city, the exposure can be considerably higher or lower. This results in negative (fig. 5b, 2 and 11 am) or positive (fig. 5a, 12:30 pm and following full hours) peaks in the exposure concentration compared to the indoor environments.

4 DISCUSSION

This study is a first attempt to develop a model approach for exposure of individual persons to airborne particles using GPS tracks. All parts of the framework required simplifications and assumptions, leading to limitations and shortcomings of the results that are discussed in this section.

In comparison with the indoor measurements, it is obvious that the indoor model sometimes over- and sometimes underestimates the measured concentration. This certainly results from using the means of the parameter distributions. The indoor model using the US PTEAM values showed a reasonable agreement with the indoor measurements except the indoor source strength for the office that was adapted in order to avoid the obvious overestimation by nearly a factor of two (fig. 3b). Certainly, the next step has to be a larger validation survey to test and adapt the model parameters on local circumstances such as building characteristics and seasonality. Using European data sets such as the existing EXPOLIS (Hänninen et al., 2004b) and RUPIOH database (Hoek et al., 2008) could be useful if values exist for Germany. Their results indicate that the air exchange could be a bit lower in Central Europe than the PTEAM values show (mean of 0.8 h^{-1} for Basel and Prague, Hänninen et al., 2004b) Also the temporal variation of factors would be interesting to investigate, as the values assessed by such large studies are time averaged and cannot be assumed to be constant over the 5 min intervals we used for calculation. Here, one major improvement could result from the use of a probabilistic approach (Zidek et al. (2005) to include the natural variability of the model parameters. Using for example realizations produced by Monte Carlo Simulations instead of single mean values, would additionally yield an estimate of the distribution of individual exposure profiles instead of single values as we do not know the exact value for each indoor environment.

The concentrations in private residences, which play an important role due to the large proportion of time (60 % per day) people spend at home (Klepeis et al., 2001), are particularly difficult to model with the used approach because of heterogeneous indoor conditions and a great range of emission sources occurring. In the residence survey, our model produced much higher PM concentrations than the measurements for the smoking event including the following four hours. For the sleeping periods, the model data were lower. Possibly, the measurement diary was not sufficiently detailed to record all ventilation events (window opened) during and after the smoking, and the number of people entering and leaving the respective room. The higher measured concentrations during the night contradict the concept of a stronger PM2.5 source during daytime due to re-suspension by humans of higher activity (Ferro et al., 2004; Morawska, 2004; Qian and Ferro, 2008). Explanations could be re-suspension of bedding or condensation of volatile organic compounds (VOC), as emitted from the sleeping person, on pre-existing particles indoors, or higher outdoor sources such as woodsmoke that were not captured by the ambient measurement station. In summary, the data of this survey alone could not explain the night-time pattern satisfactorily.

Another limiting factor lied in the diaries that only provided restricted information about indoor environments and personal behavior, so the model produces uncertain values in consequence. The complexity and accuracy of the indoor model is limited by the diary accuracy. For instance, the indoor environment is usually not described satisfactorily to apply a multi-compartment indoor model that would produce more realistic values than the simple mass balance model we used. Here a more precise quantification of the indoor activities and presence of persons in the rooms would be preferable, but difficult to obtain with the classic diary techniques. A recording camera carried by the test persons or indoor tracking systems, could lead to more detailed, post-processed diaries. Generally, an automation of extracting activity profiles from sensor data by adapting machine learning methods would be helpful to establish an easy sampling method for detailed activity patterns. Extracting transportation modes and motion patterns from GPS tracks is already a field of research (Patterson et al., 2003, Brandherm and Schwartz, 2005).

It should also be noted that the spatial distribution as estimated by annual means in the LASAT model, and adjusted with 30 min measurements, is only a rough approximation of the real situation in the city. The inclusion micrometeorological patterns could yield good results here. Also the distance to streets should be parameterized in a more detailed fashion instead of using just one pair of discrete values.

The resulting individual daily exposure profiles, as shown in fig. 5, exhibit similar dynamics and patterns as the measured personal exposure presented by Repace (2007), especially for smoking peaks. Nevertheless, the absolute values are uncertain due to the assumptions taken and existing limitations of the model approach. For instance, because the indoor model assumes dependence upon the outdoor concentration, which was partially proven by the indoor measurements, personal exposure profiles show this dependence as well. The most important factors affecting this relation are ventilation habits and indoor source strengths. During the weekend profile of test person 3 and the working day profile of test person 4, none of the indoor sources of tab. 2 occurred. Consequently, the modeled exposures are more similar to the respective outdoor concentrations as the indoor source contribution is rather small. This shows how crucial good estimates of the air exchange rate as driven by climate, ventilation systems, building type, and ventilation habits for this type of model are. The high standard deviation of all profiles shows how variable the individual exposure over the day can be. Thus, using a daily mean as exposure surrogate smoothes the pattern of exposure. For example, a very short but extremely high exposure yields a higher mean, and could eradicate the fact that the exposure is rather low for most of the time. For a verification of the model results, the personal exposures towards PM have to be monitored by using mobile, recording PM concentration measurements with a high temporal resolution. The respective techniques became available on the market just recently. Widespread application will significantly contribute to further development and evaluation of individual exposure models.

5 CONCLUSION

We showed that it is feasible to model the personal exposure to particulate matter by a relatively simple combination of existing models and measurement networks with positional information. Due to the limited resources available, the model results exhibit known limitations. On the other hand, our results are, for the moment, best estimates for indoor and outdoor conditions. The model can be further improved significantly while retaining the current architecture. The GIS environment may be developed through reduction of manual labor and introduction of automated techniques in both model parts. Thus, a much larger number of GPS profiles could be collected and used as input for the model without requiring new model adaptation. It is also possible to extent the application easily to other regions if dispersion model results and access to ambient measurements are available. The simple application and transferability is a clear advantage compared to existing individual exposure model approaches like e.g. land use regression (Jerrett et al., 2005b)

In contrast to assuming ambient stationary measurements as individual exposure estimates, the resulting personal profiles include spatial variation of the concentration while moving through the concentration field. Beside all the limitations mentioned, this is a step forward to quantify individual exposure accurately and potentially for a large number of individuals. From these outcomes, individual behavior rules could be deduced. Not each individual is influenced in the same way by mitigation measures to regulate ambient concentrations as their exposure does not depend linearly on the outdoor concentration. Individuals with higher outdoor exposure can influence their personal exposure by choosing the route, transportation mode and time for their journeys (Hertel et al., 2008). A possibility for avoiding high indoor concentrations is, for example, an adaptation of the ventilation habits. If strong indoor particle sources are present, the window should be opened to avoid accumulation of particles indoors. On the other hand, if the building is located near a busy street, or a day with extreme PM concentration occurred, and no specific indoor sources are present, the person should keep the window closed to avoid infiltration of particle fractions from outdoors. The presented basic approach could in future be easily extended to a near real-time information system for individuals.

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Table 1. Diary excerpt of a male, 19 years old student (test person 4) for a weekend day.

Location	Start time	End time	Activity	Smoker
Friend’s home	00:00	02:00	playing cards	3
Way home	02:00	02:05	biking	-
Home	02:05	10:40	sleeping	-
Home, bathroom	10:40	11:00	washing	-
Way to store	11:00	11:05	driving car	-
Store	11:05	12:25	shopping	3
Way home	12:25	12:30	driving car	-

Table 2. Used parameters for indoor microenvironments taken from the literature.

Microenvironment	a [h^{-1}]	D [h^{-1}]	p	V [m^3]	Unknown E [mg h^{-1}]	Data source
Home, day Home, night	1.02/1.5 0.80/1.5	0.39 0.39	1 1	42/104 42	1.1 1.1	PTEAM (Özkaynak et al., 1996b)
Other residences	1.02	0.39	1	104	1.1	PTEAM (Özkaynak et al., 1996b)
Office	1.02/1.5	0.39	1	45	*1.1* **0.368**	PTEAM (Özkaynak et al., 1996b) Regression (eq. (4)) with PTEAM values
University/school	1.02/1.5	0.39	1	235	1.1	PTEAM (Özkaynak et al., 1996b)
Other (public) indoor	1.02/1.5	0.39	1	235	1.1	PTEAM (Özkaynak et al., 1996b)
Pub	-	-	-	-	192 µg m-3	Bolte et al. (2008)
Restaurant	-	-	-	-	178 µg m-3	Bolte et al. (2008)
Car	-	-	-	-	Cout	Gulliver and Briggs (2003)
Bus/train	-	-	-	-	Cout*1.7	Praml & Schierl (2000)

Table 3. Strengths of short-term indoor particle sources E.

Indoor particle source	Source strength [mg h-1]	Data source
Smoking	13,7 mg cig^{-1}	PTEAM (Özkaynak et al., 1996b)
Cooking	1.7 mg min^{-1}	PTEAM (Özkaynak et al., 1996b)

Table 4. Spearman's rank correlation coefficients between the 24-hour indoor measurements and routine station measurements.

Indoor measurement	Urban background routine station	Traffic routine station
Seminar room	0.72	0.71
Office	0.26	0.62
Residence	0.11	-0.11

Table 5. Demographic data and daily mean (standard deviation) of the 5 min averaged PM2.5 exposure estimates for all six test persons.

Test person	Gender	Age	Employment status	Exposure working day	Exposure weekend day
T1	Female	23	Student, part time	35.7 (50)	78.5 (164.7)
T2 (1) T2 (2)	Female	24	Student, part time	62.1 (85.9 284. (599.3))	106.5 (136.8) 274.1 (325.2)
T3	Male	27	Full time	41.1 (46.1)	19.3 (8.3)
T4	Male	19	Pupil	24.9 (4.6)	99.7 (173.4)
T5	Female	40	Part time	34.8 (59.6)	31.1 (58.5)
T6	Male	40	Full time	23.9 (19.4)	33.0 (61.5)

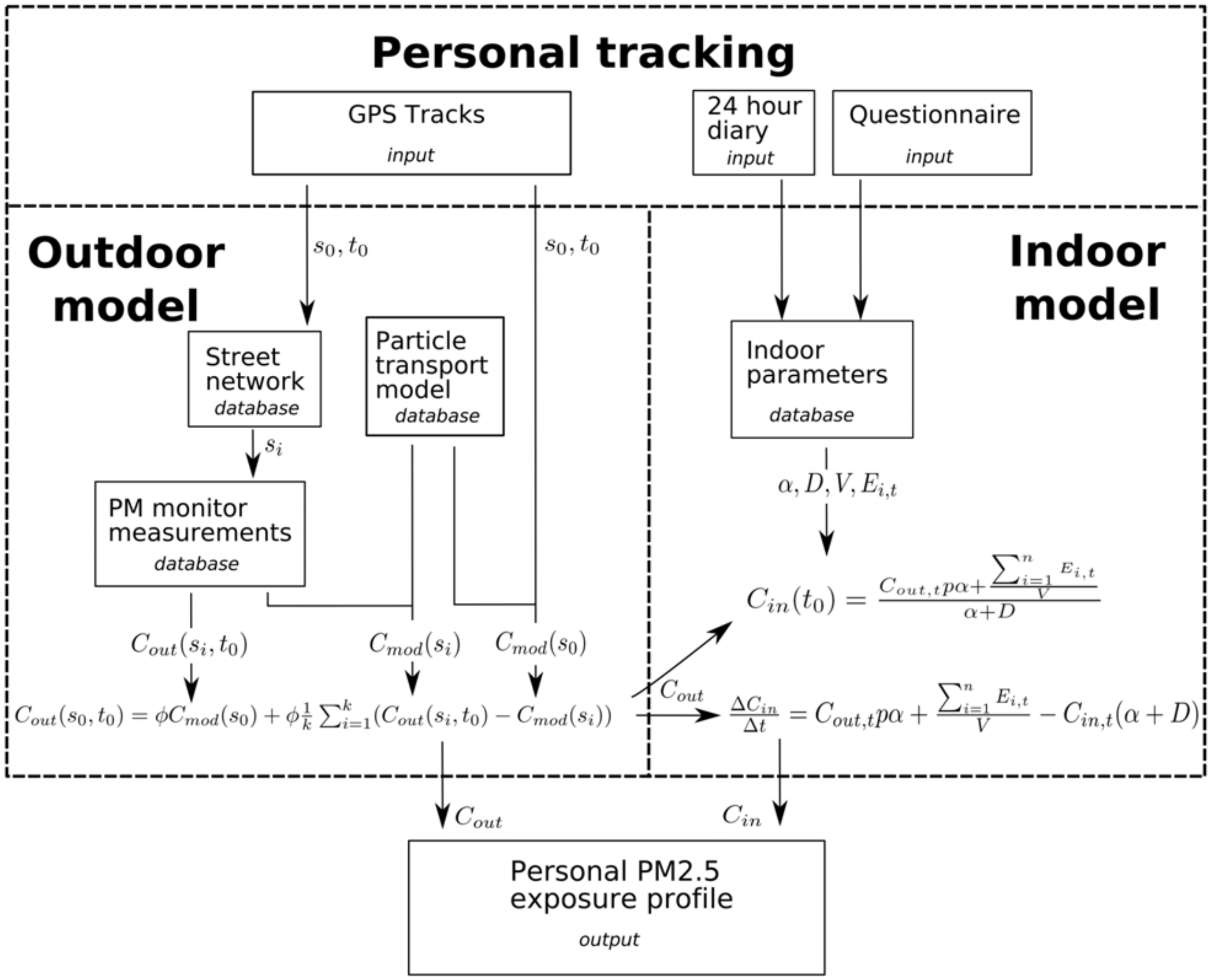


Figure 1. Exposure model data processing chain implemented in the GIS environment

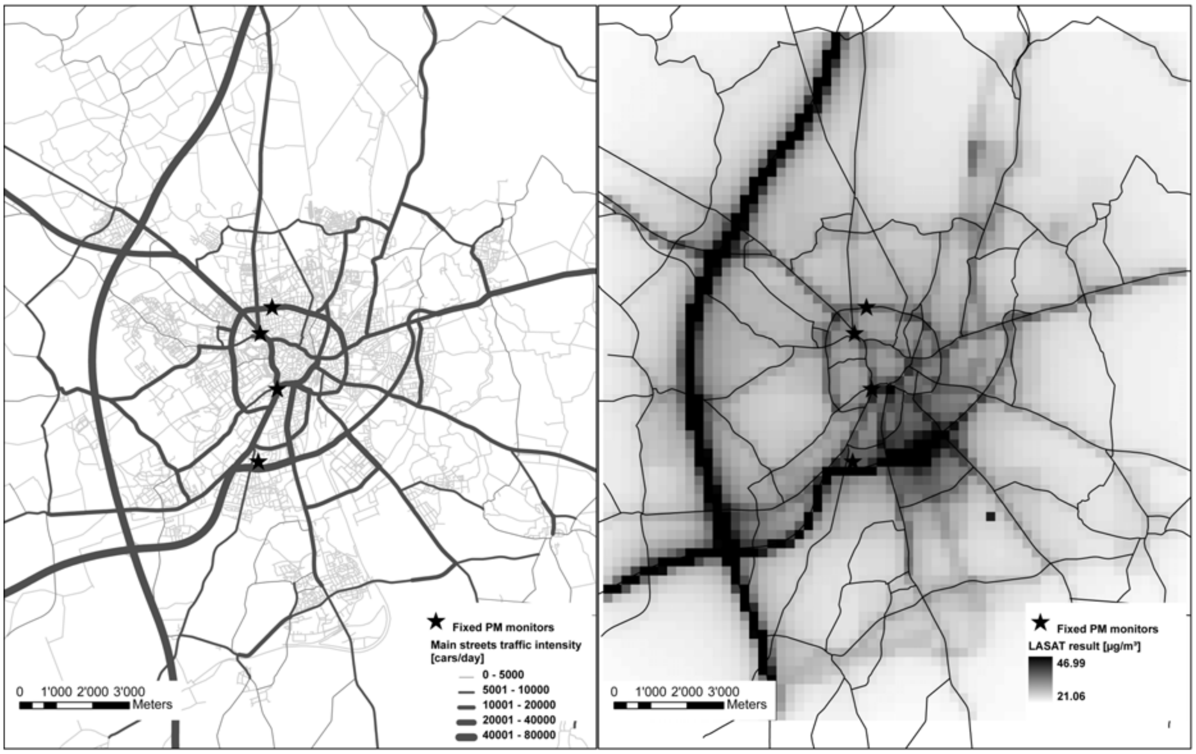
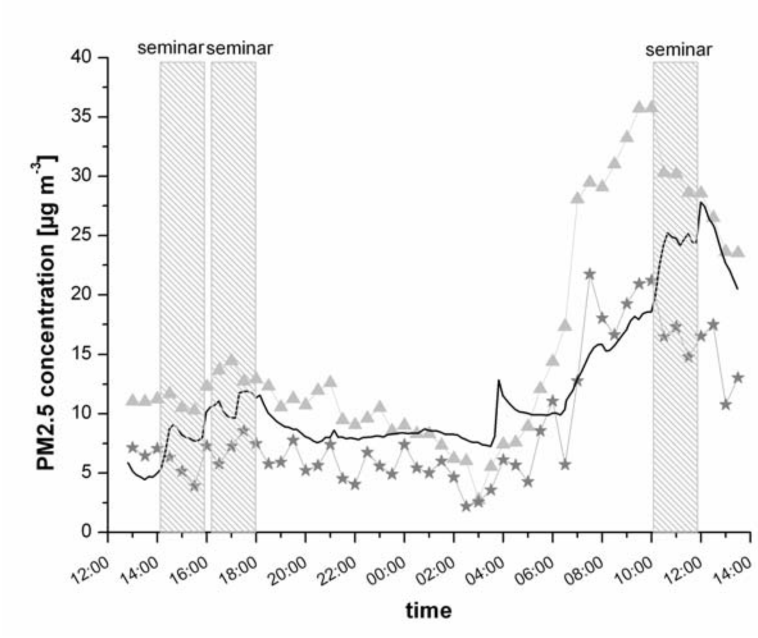
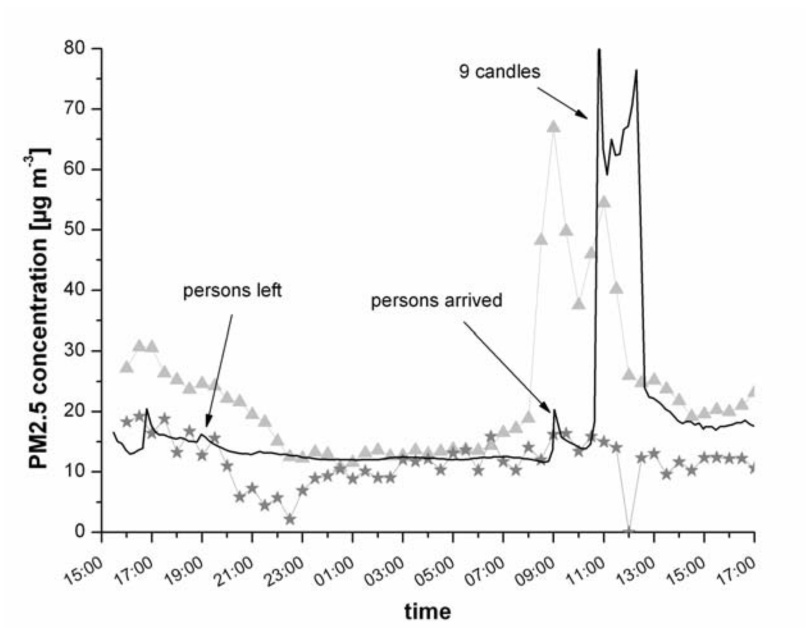


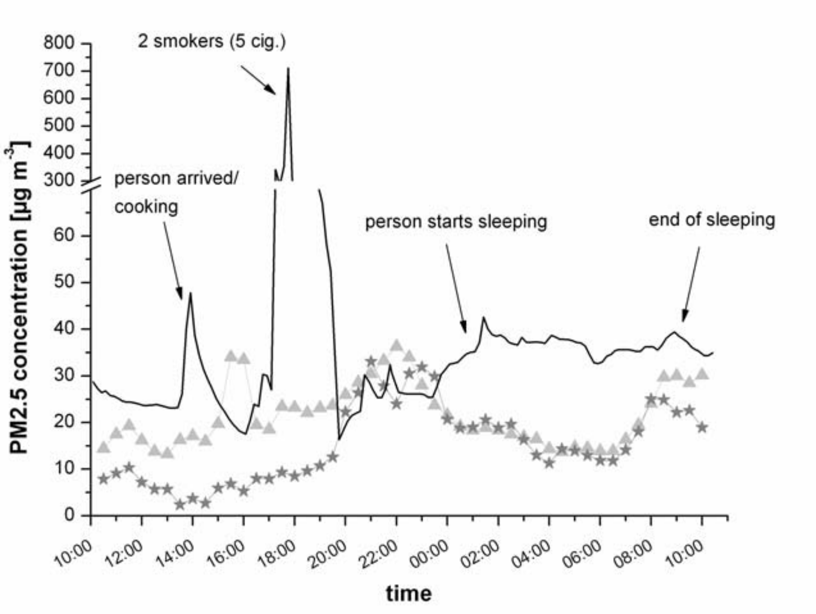
Figure 2. Map of Münster with fixed air quality monitor locations, major roads traffic density (left panel) site and LASAT PM10 concentration results (right panel).


seminar
seminar
seminar
PM2.5 concentration [µg m-3]
time

a)

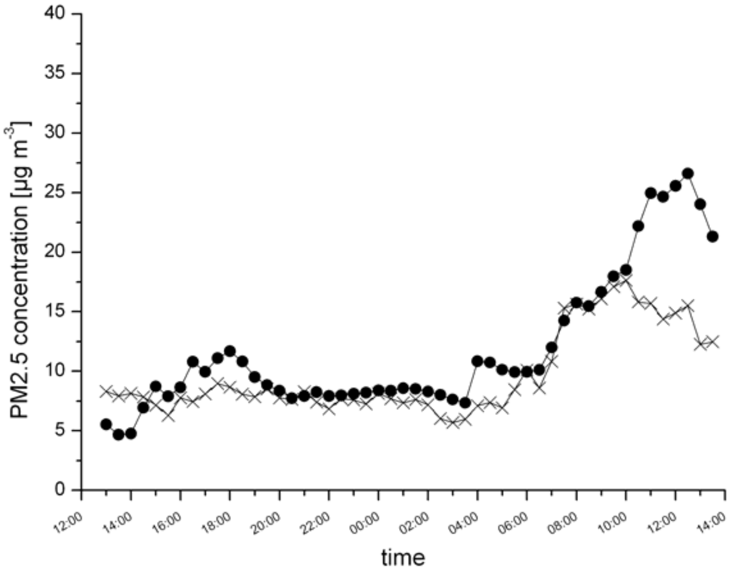

9 candles
persons left
persons arrived
PM2.5 concentration [µg m-3]
time

b)



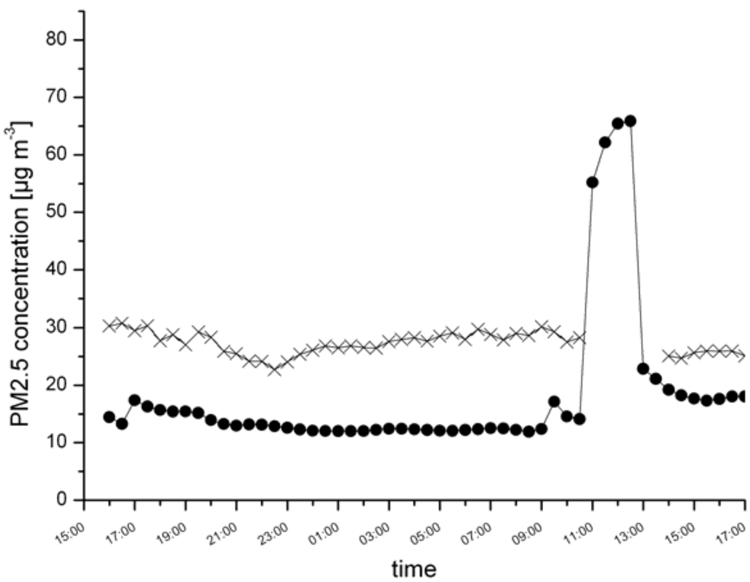
c)

Figure 3. Comparison of 10 min a) seminar room (12/11-12/12/2006), b) office (12/13-12/14/2006) and c) residence (01/25-01/26/2007) PM2.5 measurements (solid line) and respective 30 min fixed site monitor PM2.5 measurements, namely a traffic station (light grey triangles) and a background station (grey stars).



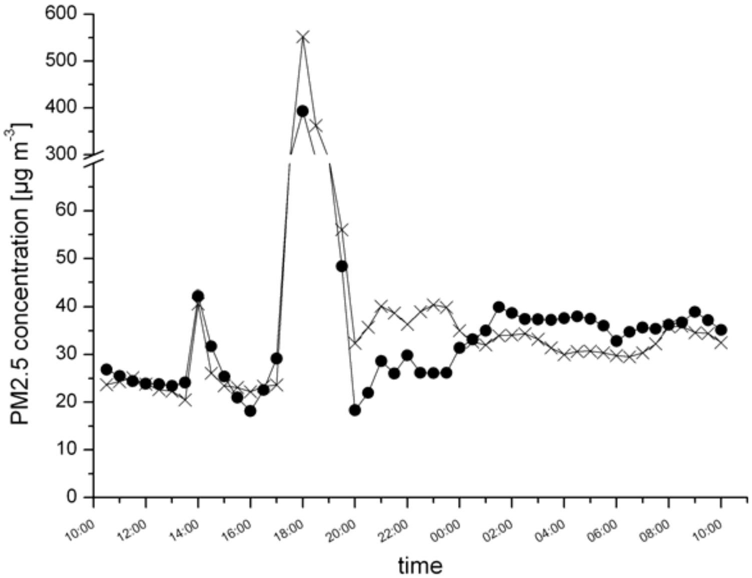
PM2.5 concentration [µg m^{-3}]
time
0
5
10
15
20
25
30
35
40
12:00
14:00
16:00
18:00
20:00
22:00
00:00
02:00
04:00
06:00
08:00
10:00
12:00
14:00

a)



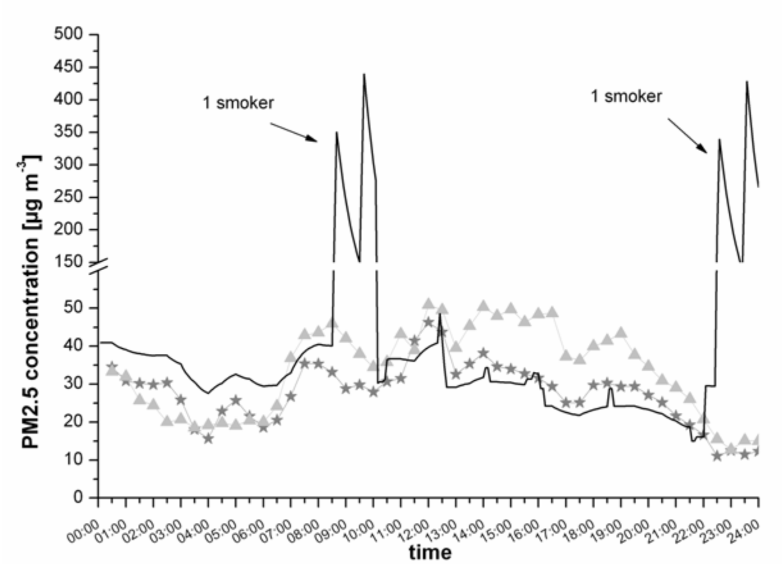
PM2.5 concentration [µg m^{-3}]
time
0
10
20
30
40
50
60
70
80
15:00
17:00
19:00
21:00
23:00
01:00
03:00
05:00
07:00
09:00
11:00
13:00
15:00
17:00

b)

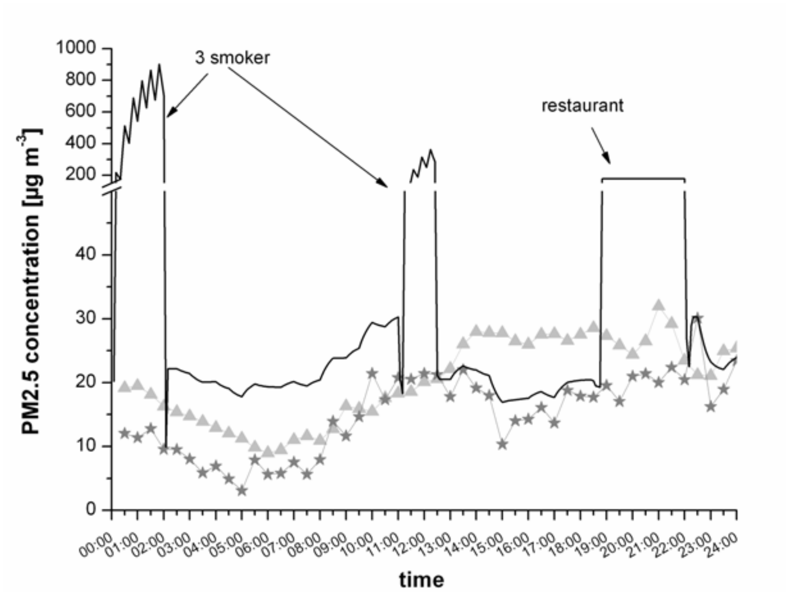


c)

Figure 4. Comparison of 30 min aggregated a) seminar room (12/11-12/12/2006), b) office (12/13-12/14/2006) and c) residence (01/25-01/26/2007) PM2.5 measurements (black circles) and modeled 30 min PM2.5 concentration (crosses) using the PTEAM parameter estimates from tab. 2 and 4.



a)



b)

Figure 5. Modeled 5 min PM2.5 concentration of a) a working day of the female smoking test person 2 and b) a weekend day of the male non—smoking test person 4 (solid lines) and corresponding 30 min fixed site monitor measurements, i.e., traffic station (light grey triangles) and background station (grey stars).

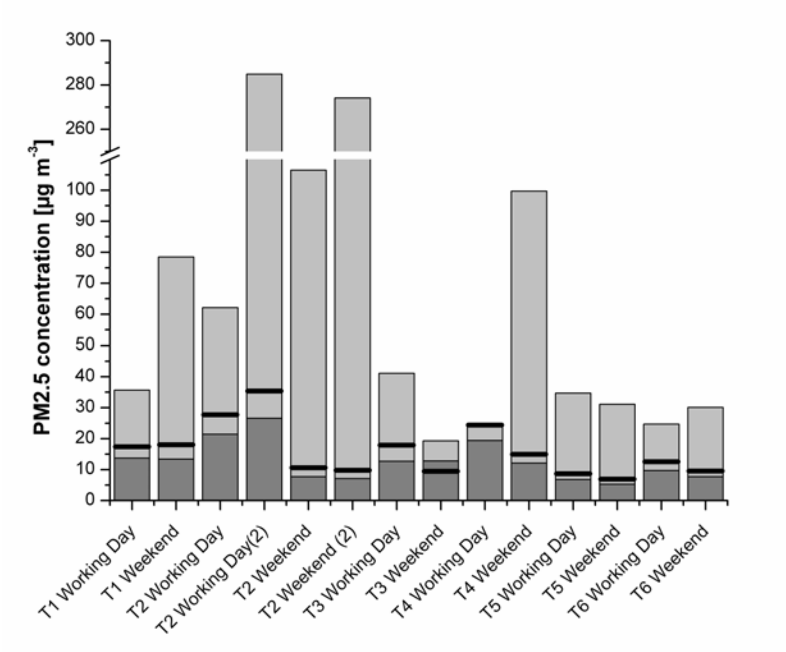


Figure 6. Comparison of daily PM2.5 means with the exposure contribution from outdoor air (dark grey) and indoor sources (light grey) of the modeled profiles and the background station measurements (black line). The averages of respective traffic station measurements were between 1.1 and 1.7 times higher than the background averages.