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Disaggregation of nation-wide dynamic population exposure estimates in The Netherlands: Applications of activity-based transport models

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ABSTRACT

Traditional exposure studies that link concentrations with population data do not always take into account the temporal and spatial variations in both concentrations and population density. In this paper we present an integrated model chain for the determination of nation-wide exposure estimates that incorporates temporally and spatially resolved information about people's location and activities (obtained from an activity-based transport model) and about ambient pollutant concentrations (obtained from a dispersion model). To the best of our knowledge, it is the first time that such an integrated exercise was successfully carried out in a fully operational modus for all models under consideration. The evaluation of population level exposure in The Netherlands to NO_2 at different time-periods, locations, for different subpopulations (gender, socio-economic status) and during different activities (residential, work, transport, shopping) is chosen as a case-study to point out the new features of this methodology. Results demonstrate that, by neglecting people's travel behaviour, total average exposure to NO_2 will be underestimated by 4% and hourly exposure results can be underestimated by more than 30%. A more detailed exposure analysis reveals the intra-day variations in exposure estimates and the presence of large exposure differences between different activities (traffic > work > shopping > home) and between subpopulations (men > women, low socio-economic class > high socio-economic class). This kind of exposure analysis, disaggregated by activities or by subpopulations, per time of day, provides useful insight and information for scientific and policy purposes. It demonstrates that policy measures, aimed at reducing the overall (average) exposure concentration of the population may impact in a different way depending on the time of day or the subgroup considered. From a scientific point of view, this new approach can be used to reduce exposure misclassification.

1. Introduction & background

Recent air-quality studies have highlighted that important differences in pollutant concentrations can occur over the day and between different locations (Wilson et al., 2005). At the same time, the location of individuals also varies over space and time causing a large geographical and temporal variation in the number of people present at any location during the day. Traditional exposure studies that link concentrations with population data however do not always take into account the temporal and spatial variations in both concentrations and population density, often because temporally resolved data are simply not available (Hertel et al., 2001).

Concerning the pollutant concentration data, most epidemiological research has focused on relating health endpoints in entire populations to pollutant concentration data from a small number of fixed site monitoring stations (e.g. Wang et al., 2008; Wu et al., 2009). Unfortunately, the measurement data from these fixed stations do not necessarily represent areas beyond their immediate vicinity. For example, Alm et al. (1998) report that only a minor fraction of the variations in personal NO_2 exposure of children was explained by concentration data obtained from stationary monitoring stations. In evaluating the exposure of the population to air pollution, the use of atmospheric dispersion models or sensor networks should therefore be preferred above the use of these fixed stations (Stein et al., 2007). Validated atmospheric dispersion models can provide more detailed information on the spatial distribution of the pollutant concentrations, allowing for more realistic exposure assessments.

Concerning the location of the people, traditional exposure analyses often rely on official address data only, implicitly assuming that people are always at home and, therefore, only exposed to pollution at their place of residence (Hertel et al., 2001). A study by

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Beckx et al. (2008, 2009a) indicated that, to establish an improved assessment of exposure, it is necessary to take into account that people move during the day and are therefore exposed to pollutant concentrations other than at their home address (i.e. a dynamic exposure assessment).

Understanding exposure variations among activities and subpopulations further advances the current state-of-the-art and might be even more important for risk management. In addition to this, a more detailed exposure analysis in terms of activities that are performed during the day (working, shopping, leisure,...) or concerning different subgroups (gender, socio-economic status,...) would provide more useful insights into the total exposure. Unfortunately, only few attempts (e.g. Kousa et al., 2002; Marshall et al., 2006; De Ridder et al., 2008b) have been made to perform such a detailed dynamic exposure assessment. Kousa et al. (2002) compared exposure distributions for different activities based on observed time-activity data for 435 adults in the Helsinki Metropolitan Area. They concluded that the average exposure to NO_2 at home and in the workplace was substantially more important than in "other" activities. Marshall et al. (2006) examined exposure differences between population subgroups and reported differences in exposure concentration between whites and non-whites in the California's South Coast Air Basin by examining geocoded activity-diaries. Part of these differences were explained by the home location, but a significant fraction of the variation in exposure concentration was due to differences in travel behaviour and different exposures accumulated during daytime activities performed at other locations. De Ridder et al. (2008b) studied impacts on traffic emissions and exposure to air pollution of long-term changes in population densities in the German-Ruhr area. However, none of these studies can provide information on large areas or entire population values because they only covered a restricted (urban) area or only a small (non-representative) sample of the population. Furthermore, these studies do not report exposure values or exposure differences on an hourly basis, while this information can be extremely useful for certain policy purposes.

In order to draw general conclusions on the exposure of the whole population, a sufficiently large dataset needs to be gathered, representing different subpopulations and time-periods in a realistic and unbiased way. Examples of exposure analyses that use synthetic population data for exposure analysis are described in Burke et al. (2001), Freijer et al. (1998) and Gulliver and Briggs (2005). In general, these studies use observed activity-travel data from different subgroups at different moments to make predictions about the travel behaviour for the entire population. Recently, a similar population simulation approach evolved in the field of transportation research. The resulting population models were originally developed to provide more insights into the travel behaviour of people and are better known as 'activity-based models' or 'activity-based transport models'. Partial and fully operational activity-based micro simulation systems include Florida's Activity Mobility Simulator (FAMOS) (Pendyala et al., 2005), the Travel Activity Scheduler for Household agents (TASHA) (Miller and Roorda, 2003) and ALBATROSS (A Learning-Based Transportation Oriented Simulation System) (Arentze and Timmermans, 2004). Recent applications of these models (e.g. Roorda et al., 2008; Timmermans and Zhang, 2009) mainly focus on their advantages for travel behaviour research, however Beckx et al. (2008, 2009a) already indicated that an activity-based model can also be used for pollutant exposure analysis by taking advantage of their ability to provide more accurate information on the location of the population. For a Dutch urban area it was demonstrated that a significant fraction of the air pollution exposure can be attributed to people moving in and out of the city center for different activities. The activity-based approach was able to provide the necessary information to account for this effect. Furthermore, trip information from the activity-based model (in the form of enriched origin–destination matrices) can be used to estimate pollutant emissions generated by these trips (Beckx et al., in press). Emissions derived from activity-based models can then be used to feed air-quality models and thus improve the quality of computed concentrations especially for transport related pollutants (Beckx et al., 2009b). In summary, activity-based models provide additional information on both receptors and pollutants that improves exposure assessments. Although the advantages of such a procedure have often been announced before (e.g. Shiftan, 2000), few real-world applications have been published.

In addition to the above cited advantages, activity-based models are not only a convenient way to derive time-location patterns of people, but they can also provide detailed information about *who* is performing *which* activities, providing details that are usually not available in exposure assessments (e.g. activities, socio-demographic details). In accordance to our previous work, the present article aims to further contribute to this line of research by exploring the use of the new attributes of an activity-based model to create a complete national exposure analysis for The Netherlands. To this end, emissions and air-quality results from an activity-based analysis of traffic streams are used and combined with dynamic population information over the entire country. The evaluation of population level exposure to NO_2 at different time-periods, locations, for different subpopulations (gender, socio-economic status) and during different activities (residential, work, transport, shopping) in The Netherlands is chosen as a case-study to point out the new features of this methodology.

The remainder of this paper is organized as follows. In the next section, the development of an activity-based exposure modelling framework in The Netherlands is described, using the activity-based model ALBATROSS to assess people's time-activity data and the AURORA air-quality model to calculate the pollutant concentrations. In Section 3 total and disaggregated exposure analysis results in The Netherlands are presented. The disaggregated exposure analysis involves both a classification by activity type and by population characteristics. Finally, we conclude this paper with some thoughts on future research.

2. Materials and methods

In a previous study (Beckx et al., in press), we used the activity-based model ALBATROSS to model activities and trips of the entire Dutch population in The Netherlands. Trip data were combined with statistical data on the Dutch fleet of passenger cars to estimate emissions and model air quality. In the current study, hourly concentration data resulting from the atmospheric dispersion modelling approach (see also Beckx et al., 2009b) were combined with hourly population density data derived from the activity-based model to provide detailed dynamic exposure assessments. In this section we briefly describe the emissions and concentration values that were used and explain the methods to perform the exposure analysis.

2.1. The study area

The study area for the components of the integrated modelling approach presented here encompasses the whole territory of The Netherlands (Western Europe). The country covers an area of approximately 42,000 km^2 with a population of around 16 million people. Exposure to air pollution is considered a major problem in The Netherlands and neighbouring regions. A European analysis estimated that the average life expectancy in The Netherlands was reduced by about one year in 2000 because of exposure to pollutants such as $PM_{2.5}$ (Amann et al., 2005). Unfortunately, current methodologies are unclear on which groups suffer the highest exposure and loss of life expectancy but proximity of residential areas to traffic has been identified as a risk factor (Beelen et al., 2008; Williams et al., 2009). In this paper we study the exposure to NO_2, a pollutant which is typical for transport and is associated with negative health effects. Concerning the time-period for the exposure analysis in this study area, the year 2005 was selected due to the availability of the necessary data for both population modelling and air-quality modelling.

2.2. Emissions

The emissions input consists of gridded two-dimensional emissions maps on an hourly basis. Traffic-related emissions for the year 2005 were obtained from a previous study (Beckx et al., in press) that evaluated the possibilities for the activity-based model ALBATROSS to model vehicle emissions using macroscopic emission functions. The use of a macroscopic emission approach is more suitable for this national application than a microscopic approach (e.g. Int Panis et al., 2006). The remainder of the transport sector emissions for The Netherlands were taken from the national Dutch pollutant emission inventory (PBL, 2008), which distinguishes between various types of road transport and emissions. The Dutch emission inventory is available on a yearly basis, and has a geographical resolution of 5×5 km^2. Traffic emissions were complemented with emissions from industry, shipping and building heating that were obtained from the E-MAP GIS tool. E-MAP performs a spatial segregation of CORINEAIR/EMEP emission inventories by using spatial surrogate data (Maes et al., 2009). Bi-linear interpolation techniques were employed to transfer the data correctly to the grid of the dispersion model 'AURORA'.

More details on the combination of the activity-based model ALBATROSS with the emission model MIMOSA can be found in Beckx et al. (in press).

2.3. Atmospheric dispersion modelling

AURORA, air-quality modelling in Urban Regions using an Optimal Resolution Approach, is a prognostic three-dimensional Eulerian model of the atmosphere (recent versions are described in De Ridder et al., 2008a). The model assesses how, after being emitted from a source, air pollutants are transported and mixed in the air, undergo physical changes and chemical reactions, generate secondary pollutants, etc. Both air pollutants in the gaseous and the particulate phase are taken into account. The model's outcome is three-dimensional concentration fields, giving an overall assessment of the air quality for the region of interest, and this from the ground up to approximately 20 km altitude.

Air-quality calculations were performed with AURORA to predict hourly NO_2 concentrations for the month of April 2005 on a 3-km resolution model domain. Validation studies on the hourly concentration values already confirmed the accurateness of the dispersion model for predicting outside NO_2 concentrations (Beckx et al., 2009b).

A full description of the air-quality modelling procedure used for this paper can be found in Beckx et al. (2009b). More detailed information on the model configuration, the chemical transformation of air pollutants and other input data (land use parameters, vegetation cover,…) can be found in De Ridder et al. (2008a). The AURORA model is also registered in the Model Documentation System of EIONET (http://air-climate.eionet.europa.eu/databases/MDS/index_html) and the "Model Inventory' database of COST 728 (http://www.mi.uni-hamburg.de/List-classification-and-detail-view-of-modelentr.567.0.html?&user_cost728_pi2[showUid]=101).

2.4. Time-activity data

The activity-based model ALBATROSS, A Learning-Based Transportation Oriented Simulation System, was developed in 2000 for the Dutch Ministry of Transportation, Public Works and Water Management as a transport demand model for policy impact analysis. It is a computational process model that relies on a set of decision rules, which are extracted from observed activity diary data, and dynamic constraints on scheduling decisions, to predict activity-travel patterns (Arentze and Timmermans, 2004). The model is able to predict for all the individuals within a population which activities are conducted, when, where, for how long, with whom, and the transport mode involved. As a result of the scheduling process in ALBATROSS, activity-travel patterns are established for all the adult individuals within the study area. The scheduling process includes the generation of a synthetic population and the assignment of activity-travel schedules to every individual within this population. Consecutive hourly cross sections of the modelled population will result in a representation of a dynamic population.

The ALBATROSS model used in the current study was estimated on approximately 10,000 person-day activity-diaries collected in a selection of regions and neighbourhoods in The Netherlands. The generated synthetic population represents information for a fraction of 30% of the households in The Netherlands and was created using demographic and socio-economic geographical data from the Dutch population and attribute data of a sample of households originating from a national survey including approximately 67,000 households (Arentze et al., 2008). To obtain information about the entire population, this population information was extrapolated and activity-travel schedules were generated for all the individuals within the Dutch population (approximately 11 million adult inhabitants), taking into account the different population fractions. The 4-digit postal code area (PCA) was chosen as the spatial unit for the location assignment procedure (with an average area of 8 km^2) and time steps of 1 h were chosen as the appropriate time unit. Information on the performed activity and the person involved was expressed and recorded as 'personhours' performed at a certain location (PCA). In Fig. 1 we present the distribution of personhours spent on different non-residential activities during an average weekday (Monday–Friday) over the entire study area. Considering the low number of non-residential activities at night in Fig. 1, it is clear that most people spend the night at home. However, during the day (between 7 am and 20 pm), non-residential activities account for a proportion of up to 60% of all activities. Performing a paid job outside the house (work) is the most frequent activity. Spending time in traffic between two activities (transport) is the second most time consuming activity before social activities and shopping activities. Considering the high number of personhours spent on non-residential activities, exposure during the day is likely to be significantly influenced by concentration differences between home and workplace and while in-transport.

More information about the detailed working of this model and the validation of its scheduling process can be found in Arentze and Timmermans (2004) and Arentze et al. (2003).

2.5. Exposure modelling

Concentrations to which people are exposed were taken from the gridcell corresponding to the location where the activity was performed. For this reason the hourly population data were converted to a grid map consistent with the ambient concentration map. A GIS software tool (ArcGIS) was used to match population data and concentration data on an hourly basis. This approach was adopted for people performing the activities "home", "work" and "shopping". For the activity "in-transport" we adopted a different

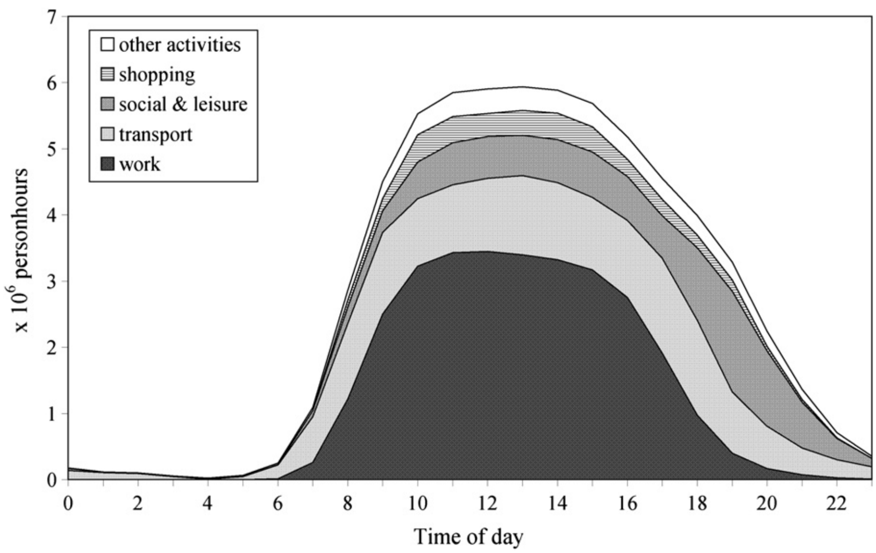

Fig. 1. The distribution of non-residential activities performed by the adult population over an average weekday in The Netherlands as simulated by the ALBATROSS model.

approach since this activity cannot be mapped onto a set of grid-cells. Other authors have circumvented this problem by either ignoring the transport activity (Hertel et al., 2001) or by simply assuming that the trajectory covered a straight line between origin and destination (Marshall et al., 2006). We have allocated the hourly average NO_2 concentration measured in the Dutch traffic-related monitoring stations to this activity (see Beckx et al., 2009b for more details). In this way we can attribute specific outdoor concentrations to each activity and exposure can be calculated in a straightforward and transparent way.

For calculating exposure we did not use correction factors to account for specific breathing rates nor did we take into account whether an activity was performed inside or outside. Indoor/outdoor ratios are notoriously inaccurate (Kousa et al., 2002) and exposure in vehicles is even harder to quantify (e.g. Berghmans et al., 2009). We have decided, for clarity and to avoid confounding our main message, to look at ambient outdoor concentrations only in this paper.

3. Results and discussion

3.1. Total exposure evaluation

In order to illustrate the hourly variations in concentrations and population, Fig. 2a, b and d, e presents concentration and population data for a selected region in the study area (the Amsterdam region) at two different time-periods. Similar geographic illustrations can of course be presented for the entire study area (The Netherlands). The Amsterdam region is an attractive city to live, work, shop, or recreate which causes a large inflow of people during the day. As an example the data values for a night period and an afternoon period are presented for a day that was selected randomly out of the entire dataset. A presentation of random chosen values was preferred above showing average concentration and population values to emphasize that the study takes into account these distinct hourly values for the exposure calculation. The resulting computed exposure values for the selected time-periods are presented in Fig. 2c and f. The population exposure was calculated by multiplying the concentration value ($\mu g\ m^{-3}$) from the dispersion model and the corresponding population value (personhours).

The mean exposure concentrations estimated by this new 'dynamic' approach for the entire Dutch study area in the month of April 2005 were first compared to results of a traditional 'static' approach (departing from residential data only and thus implicitly assuming that people are always at home). The exposure results were examined by time of day (hourly basis) to gain more insight into 'when' the largest differences between both approaches occur. Fig. 3 clearly shows that there is no significant difference between the traditional static approach and our new dynamic assessment between 8 pm and 6 am. Since, at night, the dynamic population approximates the residential population this conclusion is quite straightforward. During the day (6 am–3 pm) the dynamic exposure assessment yields a much higher estimate for the exposure compared to the static mean exposure concentration with aberrations of up to 35% ($p < 0.05$; paired two-sided t-test). At that time, a large part of the dynamic population will be performing out-of-home-activities (see Fig. 1) and, apparently, these non-residential activities occur at locations with higher NO_2 concentrations. In the early evening (5 pm–7 pm) however the static mean exposure concentration presents slightly higher exposure values than the dynamic approach, indicating that the NO_2 concentrations near the residential locations are higher than in other areas at that time. In the late evening the differences between both approaches disappear again.

Comparing the weighted daily exposure of the dynamic approach concentration relative to the static exposure concentration results in an overall difference of approximately 4%. Although relative differences during some hours are much larger, these large differences tend to occur when concentrations are relatively low and vice-versa. Our result implies that, by neglecting people's activity-travel behaviour the exposure will be underestimated by approximately 4% on average. This is consistent with the results of Marshall (2006) who also concluded that taking into account travel patterns increases estimates of exposure for traffic-related pollutants (+5% for benzene and +8% for diesel $PM_{2.5}$). The fact that a dynamic exposure analysis yields a higher estimate of exposure is linked to the fact that workplaces, traffic activities and shopping areas tend to be located in (urban) areas that have on average higher concentrations. While the differences may look small at first, we should consider that many national measures and plans to reduce transport related air pollution will only change exposure by a fraction of this amount. Present European policies (EU Directive 2008/50/EC),

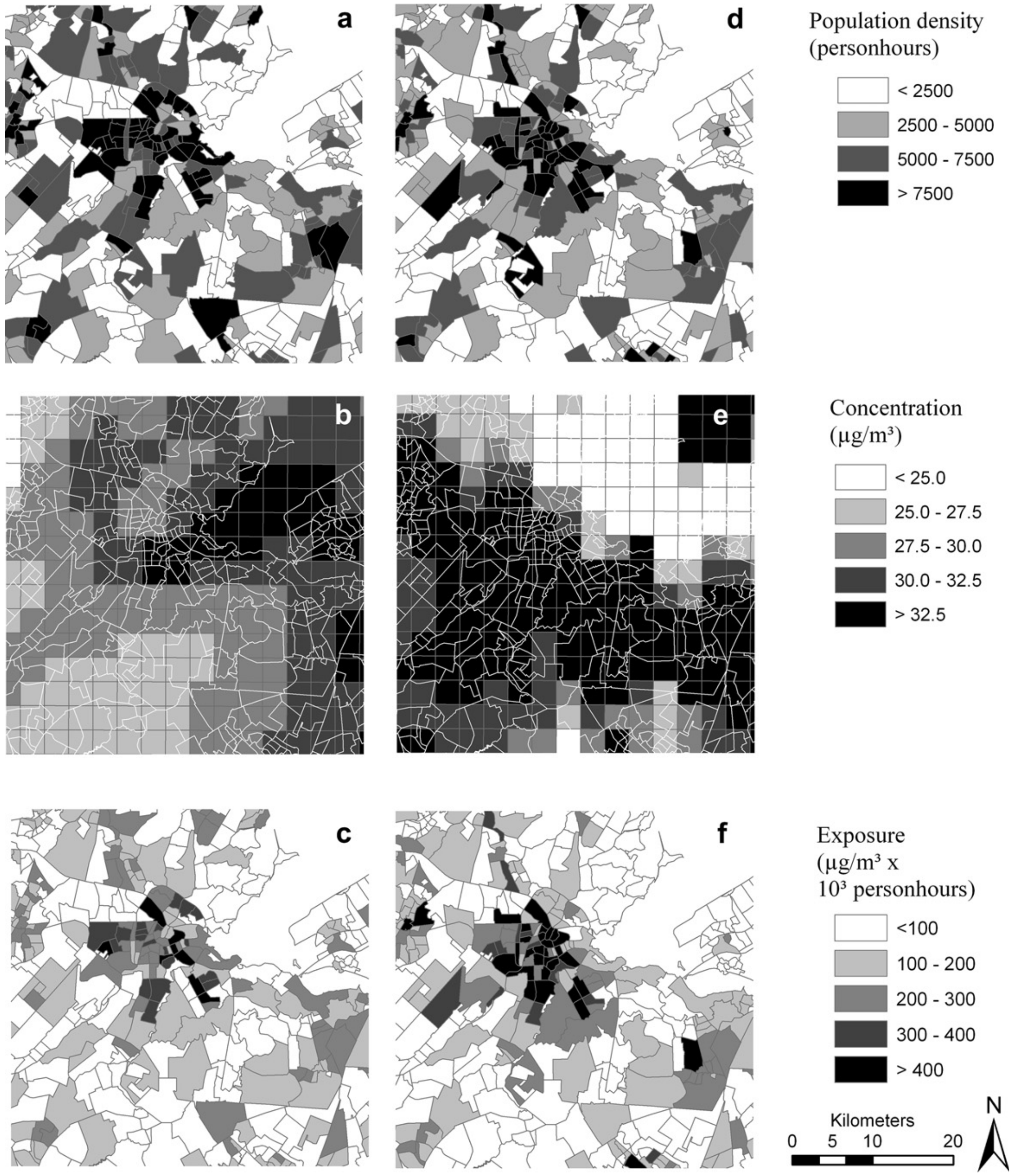

Fig. 2. (a)–(f) The predicted density of population (a,d), ambient pollutant concentrations of NO_2 (b,e) and the exposure of the population to NO_2 (c,f), evaluated for two randomly selected moments, both on Tuesday the 19th of April 2005. The maps on the left side (a–c) present values at 2 am while the maps on the right side (d–f) correspond to the values predicted for the 2 pm time-period. The size of the depicted area is 2000 km^2.

designed to reduce exposure to air pollution aim for a 5–20% reduction depending on the area. Our assessment indicates that traditional exposure assessment methods are probably not accurate enough to develop efficient policies to meet this requirement.

3.2. Disaggregated exposure analysis

In addition to conclusions that have been drawn in the section above, the true power of activity-based dynamic exposure modelling lies in identifying subgroups in the population and in activities that are associated with higher pollutant concentrations. No other transportation model than the activity-based paradigm is capable of doing this. To this end, we present a disaggregation of the exposure concentration by different subcategories in the next section.

3.2.1. Exposure by activity

Using activity-based modelling as the basis of exposure assessments enables us to disaggregate exposure for different activities. Because different activities are performed in different areas (postal areas in this case-study) each with its own concentration profile (on an hourly basis), different activities can be associated with different average concentrations. This is illustrated in Fig. 4 for NO_2 concentrations on an average weekday in April 2005. General modelled concentrations vary between 20 and 80 NO_2 μg m^{-3} for most locations with a distinct peak in the

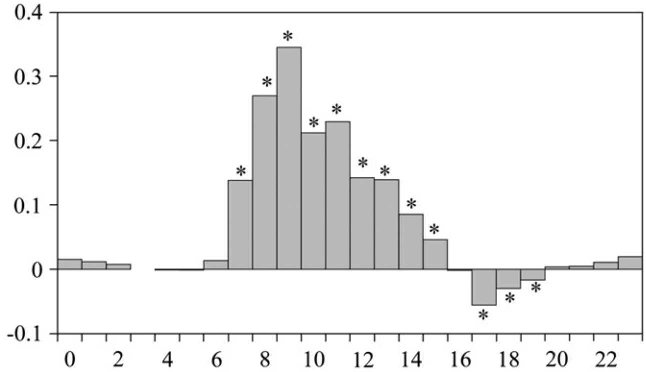

Fig. 3. Dynamic exposure estimates relative to exposure concentrations from a static approach. Relative differences for NO_2 per time of day for an average weekday in April 2005. The asterisks mark the hours with significant differences between both approaches ($p < 0.05$; paired 2-sided t-test).

morning and a protracted peak in the evening. Concentrations associated with work activities are consistently higher than concentrations associated with home-activities. Exposure while shopping only occurs during opening hours and shopping areas are characterized by intermediary NO_2 concentrations when compared to residential areas or workplaces. Average outdoor concentrations of NO_2 encountered while being in-transport are often much higher than elsewhere, except in the late afternoon.

In Fig. 5 the estimated exposure concentrations for different activities are presented relative to the dynamic exposure concentrations. The dynamic exposure concentration (expressed relative to the static exposure in Fig. 3) can be considered as the weighted average of all the activity-specific exposure concentrations (taking into account the number of personhours spent on each activity). Differences for people working at night are not statistically significant because of low numbers and are therefore not shown. Shopping activities only occur between 8 am and 20 pm. Fig. 5 clearly shows that between 6 am and 2 pm the mean exposure concentration at home, at the workplace or in a shopping area is lower than the mean exposure concentration over the entire population. On the other hand, the exposure concentration of people in-transport is, on average, much higher than the mean population exposure. In the early evening the analysis yields an opposite observation.

3.2.2. Exposure by subpopulation

Another interesting feature of activity-based models is their ability to retain demographic and socio-economic data of the people making trips and performing activities. In this way the exposure analysis can be disaggregated by different population subgroups. In this paper we show two examples to illustrate this point: an analysis by gender and by socio-economic classification. In Fig. 6 we have plotted the exposure differences (relative to the total dynamic exposure concentration) by hour of day. The exposure patterns of the male and the female population display opposite values. Since the exposure values for men and women contribute almost equally to the total dynamic exposure values (there are only slightly more women in the Dutch population than men), this observation is rational. In the early morning men seem to be exposed to higher NO_2 concentrations compared to the mean population exposure values, conversely women are less exposed at that moment. Exposure differences up to 12% were recorded in the morning, indicating that, at that time, men perform activities at locations with much higher concentrations than women. Since men appear to travel earlier in the morning than women (travel results not shown here) and morning traffic concentrations appear to be quite high (see Fig. 4) the difference in the morning can be explained by a different travel behaviour. Exposure differences between 9 and 11 am are reversed because at that time more women than men travel exposing themselves to higher concentrations than those experienced by men (many of whom are then subjected to workplace concentration levels). In the afternoon men experience once again a slightly higher exposure which can be explained by the fact that more men than women have a paid job outside the house especially in the afternoon (more women work part-time jobs) and the workplace exposure concentrations are always slightly higher than at home. The overall (24 h) difference in exposure between men and women is 1.16% (i.e. exposure of men relative to women), consistent with the findings from Marshall (2008) who also reported that these differences in pollutant intake rate will be even more explicit when taking into account gender-specific breathing rates (men: 14.9 $m^3\ d^{-1}$; women: 10.5 $m^3\ d^{-1}$).

In the second exposure analysis by subpopulation we used a similar disaggregated exposure analysis to distinguish the exposures of people of different socio-economic groups. Within the ALBATROSS model people (households) are categorised into four socio-economic classes (SEC) according to their income. By means of example we compared the exposure concentrations between

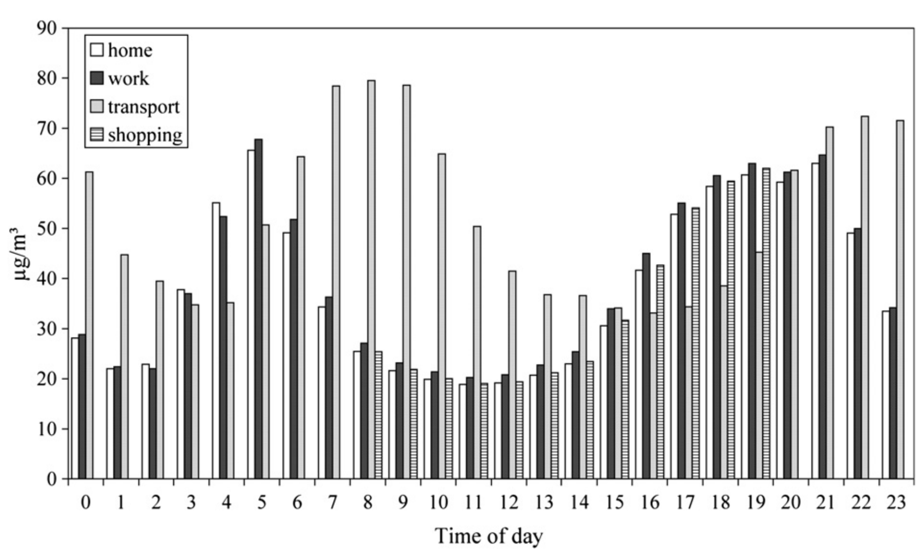

Fig. 4. NO_2 exposure concentrations per time of day for different activities on an average weekday in April 2005.

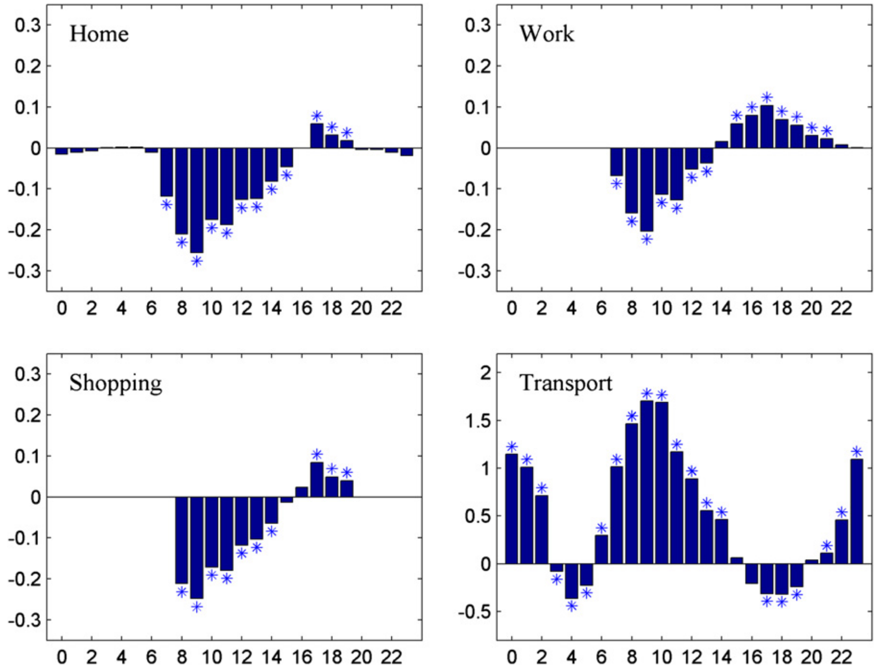

Fig. 5. Estimated mean exposure concentration for each subgroup (activity) relative to the overall mean (dynamic) population exposure concentration. Values are presented per hour for the exposure to NO_2 on an average weekday in April 2005. The horizontal axis presents the time of day per hour. Note that a different ordinate scale was used for the transport activity. The asterisks mark the hours with significant differences between both approaches ($p < 0.05$; paired 2-sided t-test).

people from the lowest SEC (income less than average) and people belonging to the highest SEC (income more than double of average). As can be seen in the bottom graphs from Fig. 6 people belonging to the lowest socio-economic group appear to be exposed to slightly higher concentrations of NO_2 throughout the day, but there is a large variation within the day. Differences of up to 3% in the early morning/night are statistically significant. This effect is caused by concentration differences in the residential areas of both groups, a phenomenon which was also described by Marshall (2008). It is interesting to see the opposite during the morning rush hour. People belonging to the highest SEC then have a higher exposure, an effect that is caused by the fact that they are more likely to be driving to work, exposing themselves to the higher traffic concentrations. This offsets most of the original difference between both classes and hence the overall (24 h) difference between both subgroups is small (0.84%) and not statistically significant.

It is likely that the true difference in exposure between different socio-economic groups is even larger than the value that was

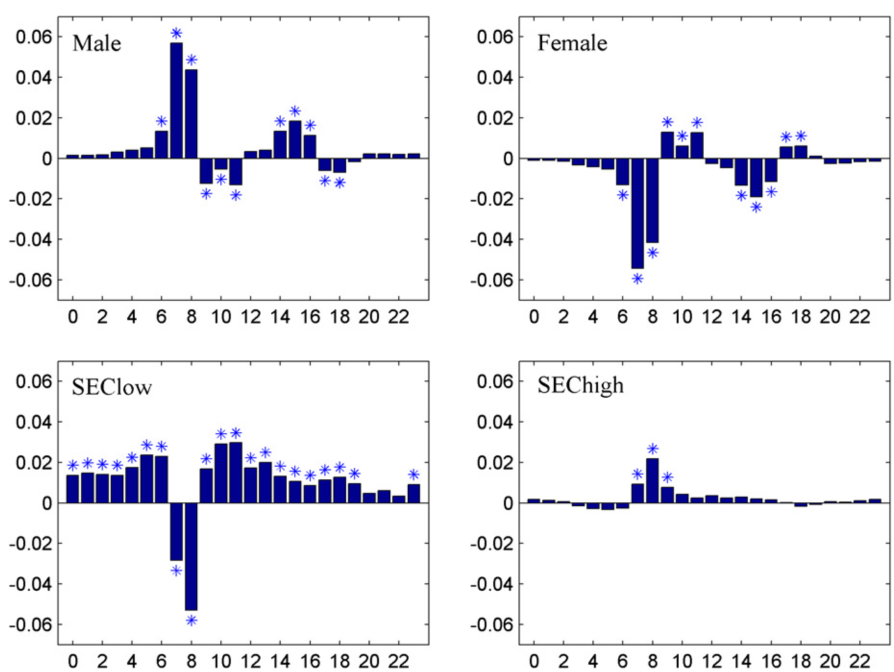

Fig. 6. Estimated mean exposure concentration for each subgroup (population) relative to the overall mean (dynamic) population exposure concentration. Values are presented per hour for the exposure to NO_2 on an average weekday in April 2005. The horizontal axis presents the time of day per hour. The asterisks mark the hours with significant differences between both approaches ($p < 0.05$; paired 2-sided t-test).

presented here. It is well known that lower income groups tend to live in cheaper houses, including those that lose value because of higher noise levels. Differences in noise levels and important differences in NO_2 concentrations are known to occur over much smaller distances than the resolution of our present model version (3×3 km). It is therefore likely that we have underestimated this difference. On the other hand is it remarkable that we can observe this phenomenon even at the national level.

4. Conclusion

In this paper we have presented an integrated model chain to estimate the population exposure to NO_2 based on activities and associated trips. For the first time to our knowledge an activity-based transport model was integrated with concentration data from an air-quality model, to perform such a nation-wide dynamic exposure assessment to air pollution. The dynamic exposure analysis from the activity-based approach yielded higher total exposure estimates than the conventional static assessment that assumes people are always at home. Depending on the perspective taken, differences can either said to be small (approximately 4% over the entire population) or rather important (from an air-quality policy perspective).

A disaggregated analysis of the population exposure to NO_2 revealed that exposure may vary between activities and between subpopulations. Concerning the classification by activity, highest exposure concentrations were estimated in-transport, followed by workplaces, shopping areas and home-activities. When neglecting the exposure during non-residential activities total exposure values will be underestimated during the day. We also performed an analysis on two population classifications: one by gender and another by socio-economic status. The overall (24 h) relative exposure difference between men and women was small but large intra-day differences appeared due to a different activity-travel behaviour (e.g. more men participate in the morning traffic peak). An analysis by SEC revealed that people from the lowest SEC are exposed to slightly higher NO_2 concentrations during the day compared to the mean population exposure except in the early morning. Both the home location (living in more polluted areas) and the travel behaviour (not participating in the morning traffic peak) explain these differences.

This kind of multidisciplinary approach presented in this paper, using a transport model for air-quality purposes, is not only innovative from a scientific and methodological perspective, but it also offers advantages for policy makers. It enables them to take into account that trips both cause transport related emissions and at the same time change the distribution and attributes of the population which will result in different exposure estimates. The availability of activity-based models for exposure analysis therefore opens up a myriad of possibilities for innovative policies and measures. Policy makers will be able to design measures aimed at reducing the exposure at the most important sites, at the most critical times and for selected population groups. These efforts may partly coincide with currently implemented measures to meet general air-quality standards. However, in addition to this, we expect that new policies can especially be made more effective in reducing health impacts. In any case, policies in other domains which nowadays risk to offset environmental policies can be screened on their environmental effects before being implemented.

Future research will continue to pave this way for policy making, by adopting the new approach presented in this paper as a policy instrument to study the impact of different societal trends or specific policy measures that have an indirect impact on traffic flows. Examples that are current being studied include the aging of European populations (which impacts on their travel and activity patterns and hence on their exposure) and the impact of institutional constraints like widening of shop opening hours (which tend to shift traffic to the early morning and late evening and hence changes the temporal concentration profile of transport related pollutants). Further, the disaggregated population exposure information will be used to refine the health effects resulting from this exposure. By taking into account the estimated breathing rate (depending on age, gender, activity level,...) the inhaled dose (and the resulting health effects) during each activity can be assessed more accurately.

References

Alm, S. , Mukala, K. , Pasanen, P. , Tiittanen, P. , Ruuskanen, J. , Tuomisto, J. , Jantunen, M.J. , 1998. Personal NO_2 exposures of preschool children in Helsinki. Journal of Exposure Analysis and Environmental Epidemiology 8, 79–100.

Amann, M., Bertok, I., Cabala, R., Cofala, J, Heyes, C., Gyarfas, F., Klimont, Z., Schöpp, W., Wagner, F., 2005. CAFE Scenario Analysis Report No. 6. A final set of scenarios for the clean air for Europe programme, Final report. Available on-line http://ec.europa.eu/environment/archives/air/cafe/activities/pdf/cafe_scenario_report_6.pdf (accessed March 2009).

Arentze, T. , Hofman, F. , Timmermans, H. , 2003. Reinduction of ALBATROSS decision rules with pooled activity-travel diary data and an extended set of land use and cost-related condition states. Transportation Research Record 1831, 230–239.

Arentze, T. , Timmermans, H. , 2004. ALBATROSS: a learning-based transportation oriented simulation system. Transportation Research Part B: Methodological 38, 613–633.

Arentze, T. , Timmermans, H. , Hofman, F. , 2008. Creating synthetic household populations: problems and approach. Transportation Research Record 2014, 85–91.

Beckx, C. , Torfs, R. , Arentze, T. , Int Panis, L. , Janssens, D. , Wets, G. , 2008. Establishing a dynamic exposure assessment with an activity-based modeling approach: methodology and results for the Dutch case study. Epidemiology 19, S378–S379.

Beckx, C., Arentze, T., Int Panis, L., Janssens, D., Vankerkom, J., Wets, G. An integrated activity-based modelling framework to assess vehicle emissions: approach and application. Environment and Planning B: Planning and Design, in press.

Beckx, C. , Int Panis, L. , Arentze, T. , Janssens, D. , Torfs, R. , Broekx, S. , Wets, G. , 2009a. A dynamic activity-based population modelling approach to evaluate exposure to air pollution: methods and application to a Dutch urban area. Environmental Impact Assessment Review 23, 179–185.

Beckx, C., Int Panis, L., Van De Vel, K., Arentze, T., Janssens, D., Wets, G, 2009b. The contribution of activity-based transport models to air quality modelling: a validation of the ALBATROSS – AURORA model chain. Science of the Total Environment, 407, 3814–3822.

Beelen, R. , Hoek, G. , Van Den Brandt, P. , Goldbohm, R. , Fischer, P. , Schouten, L.J. , Armstrong, B. , Brunekreef, B. , 2008. Long-term exposure to traffic-related air pollution and lung cancer risk. Epidemiology 19, 702–710.

Berghmans, P. , Bleux, N. , Int Panis, L. , Mishra, V.K. , Torfs, R. , Van Poppel, M. , 2009. Exposure assessment of a cyclist to PM10 and ultrafine particles. Science of the Total Environment 407, 1286–1298.

Burke, J.M. , Zufall, M.J. , Ozkaynak, H. , 2001. A population exposure model for particulate matter: case study results for PM2.5 in Philadelphia, PA. Journal of Exposure Analysis and Environmental Epidemiology 11, 470–489.

De Ridder, K. , Lefebre, F. , Adriaensen, S. , Arnold, U. , Beckroege, W. , Bronner, C. , Damsgaard, O. , Dostal, I. , Dufek, J. , Hirsch, J. , Int Panis, L. , Kotek, Z. , Ramadier, T. , Thierry, A. , Vermoote, S. , Wania, A. , Weber, C. , 2008a. Simulating the impact of urban sprawl on air quality and population exposure in the German Ruhr area. Part I: reproducing the base state. Atmospheric Environment 42, 7059–7069.

De Ridder, K. , Lefebre, F. , Adriaensen, S. , Arnold, U. , Beckroege, W. , Bronner, C. , Damsgaard, O. , Dostal, I. , Dufek, J. , Hirsch, J. , Int Panis, L. , Kotek, Z. , Ramadier, T. , Thierry, A. , Vermoote, S. , Wania, A. , Weber, C. , 2008b. Simulating the impact of urban sprawl on air quality and population exposure in the German Ruhr area. Part II: development and evaluation of an urban growth scenario. Atmospheric Environment 42, 7070–7077.

Freijer, J.I. , Bloemen, H.J.Th. , de Loos, S. , Marra, M. , Rombout, P.J.A. , Steentjes, G.M. , van Veen, M.P. , 1998. Modelling exposure of the Dutch population to air pollution. Journal of Hazardous Materials 61, 107–114.

Gulliver, J. , Briggs, D.J. , 2005. Time-space modeling of journey-time exposure to traffic-related air pollution using GIS. Environmental Research 97, 10–25.

Hertel, O. , De Leeuw, A.A.F. , Nielsen, O. , Jensen, S.S. , Gee, D. , Herbarth, O. , Pryor, S. , Palmgren, F. , Olsen, E. , 2001. Human exposure to outdoor air pollution (IUPAC Technical Report). Pure and Applied Chemistry 73, 933–958.

Int Panis, L. , Broekx, S. , Liu, R. , 2006. Modelling instantaneous traffic emission and the influence of traffic speed limits. Science of the Total Environment 371, 270–285.

Kousa, A. , Kukkonen, J. , Karppinen, A. , Aarnio, P. , Koskentalo, T. , 2002. A model for evaluating the population exposure to ambient air pollution in an urban area. Atmospheric Environment 36, 2109–2119.

Maes, J. , Vliegen, J. , Van de Vel, K. , Janssen, S. , Deutsch, F. , De Ridder, K. , Mensink, C. , 2009. Spatial surrogates for the disaggregation of CORINAIR emission inventories. Atmospheric Environment 43, 1246–1254.
Marshall, J.D. , Granvold, P.W. , Hoats, A.S. , Mckone, T.E. , Deakin, E. , Nazaroff, W.W. , 2006. Inhalation intake of ambient air pollution in California's South Coast Air Basin. Atmospheric Environment 40, 4381–4392.
Marshall, J.D. , 2008. Environmental inequality: air pollution exposures in California's South Coast Air Basin. Atmospheric Environment 42, 5499–5503.
Miller, E. , Roorda, M.J. , 2003. A Prototype model of 24-hour household activity scheduling for the Toronto area. Transportation Research Record 1831, 114–121.
PBL, 2008. Pollutant Release and Transfer Register. www.emissieregistratie.nl (Last visited in November 2008).
Pendyala, R.M. , Kitamura, R. , Kikuchi, A. , Yamamoto, T. , Fujii, S. , 2005. Florida activity mobility simulator. Overview and preliminary validation results. Transportation Research Record 1921, 123–130.
Roorda, M.J. , Miller, E.J. , Habib, K.M.N. , 2008. Validation of TASHA: a 24-h activity scheduling microsimulation model. Transportation Research Part A: Policy and Practice 42, 360–375.
Shiftan, Y. , 2000. The advantage of activity-based modelling for air-quality purposes: theory vs practice and future needs. Innovation 13, 95–110.
Stein, A.F. , Isakov, V. , Godowitch, J. , Draxler, R.R. , 2007. A hybrid modeling approach to resolve pollutant concentrations in an urban area. Atmospheric Environment 41, 9410–9426.
Timmermans, H.J.P. , Zhang, J. , 2009. Modeling household activity travel behavior: examples of state of the art modeling approaches and research agenda. Transportation Research Part B: Methodological 43, 187–190.
Wang, S.X. , Zhao, Y. , Chen, G.C. , Wang, F. , Aunan, K. , Hao, J.M. , 2008. Assessment of population exposure to particulate matter pollution in Chongqing, China. Environmental Pollution 153, 247–256.
Williams, L.A. , Ulrich, C.M. , Larson, T. , Wener, M.H. , Wood, B. , Campbell, P.T. , Potter, J.D. , Mctiernan, A. , De Roos, A.J. , 2009. Proximity to traffic, inflammation and immune function among women in the Seattle Washington Area. Environmental Health Perspectives 117, 373–378.
Wilson, J.G. , Kingham, S. , Pearce, J. , Sturman, A.P. , 2005. A review of intraurban variations in particulate air pollution: implications for epidemiological research. Atmospheric Environment 39, 6444–6462.
Wu, J. , Houston, E. , Lurmann, F. , Ong, P. , Winer, A. , 2009. Exposure of PM2.5 and EC from diesel and gasoline vehicles in communities near the Ports of Los Angeles and long Beach, California. Atmospheric Environment 43, 1962–1971.