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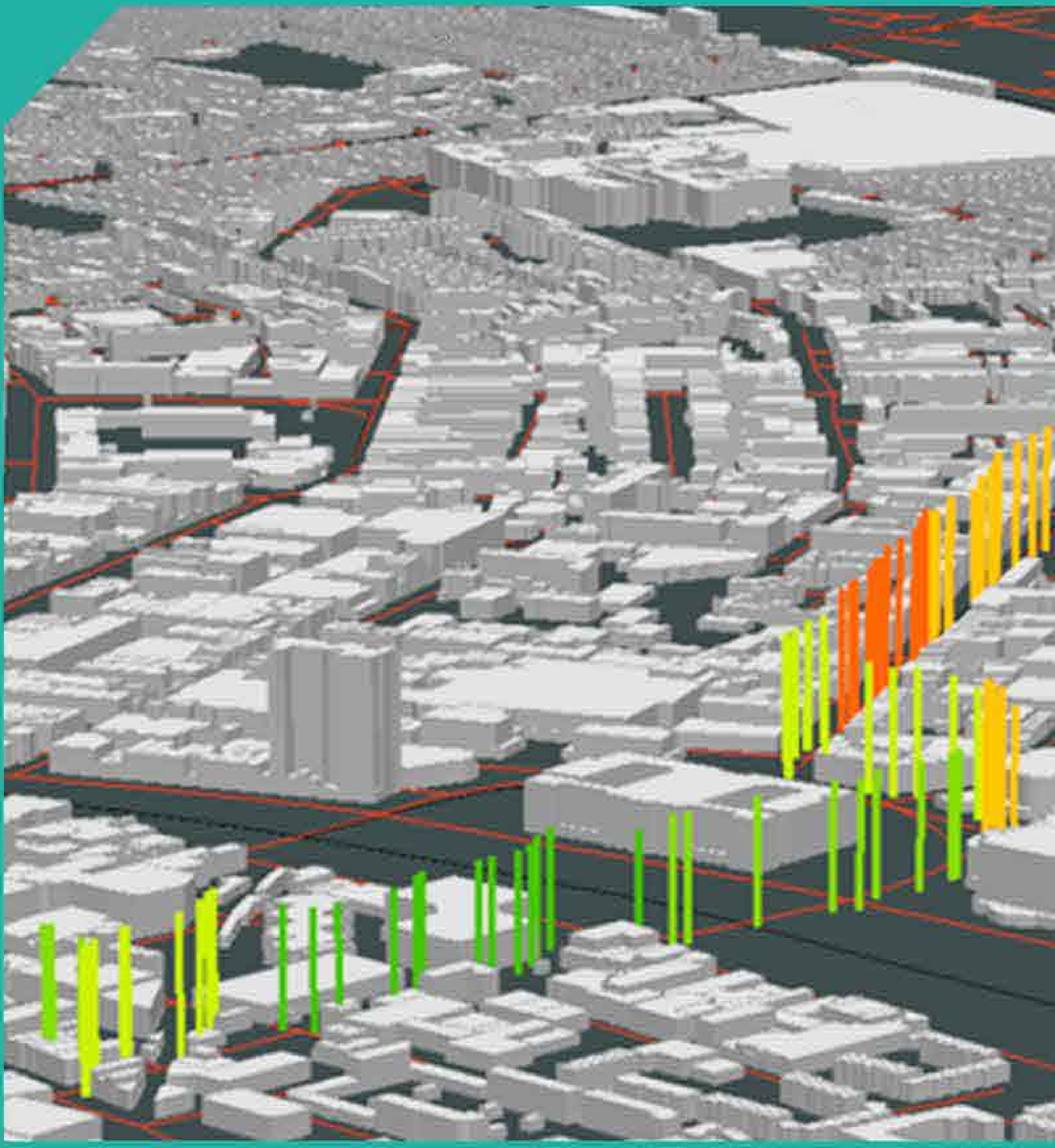
PALM: A Personal Activity–Location Model of Exposure to Air Pollution

Authors:
Brian Broderick, Miriam Byrne, Aonghus McNabola, Laurence Gill, Francesco Pilla, James McGrath and Andrew McCreddin



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Prepared for the Environmental Protection Agency

by

Trinity College Dublin and
National University of Ireland Galway

Authors:

Brian Broderick, Miriam Byrne, Aonghus McNabola, Laurence Gill, Francesco Pilla, James McGrath and Andrew McCreddin

ENVIRONMENTAL PROTECTION AGENCY
An Ghníomhaireacht um Chaomhnú Comhshaoil
PO Box 3000, Johnstown Castle, Co. Wexford, Ireland

Telephone: +353 53 916 0600 Fax: +353 53 916 0699
Email: info@epa.ie Website: www.epa.ie

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DISCLAIMER

The EPA Research Programme addresses the need for research in Ireland to inform policymakers and other stakeholders on a range of questions in relation to environmental protection. These reports are intended as contributions to the necessary debate on the protection of the environment.

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Details of Project Partners

Prof. Brian Broderick
Department of Civil, Structural and Environmental Engineering
School of Engineering
Trinity College Dublin
Dublin 2
Ireland
Tel.: +353 1 8962348
Email: bbrodrck@tcd.ie

Dr Miriam Byrne
School of Physics
National University of Ireland Galway
Galway
Ireland
Tel.: +353 91 524411
Email: miriam.byrne@nuigalway.ie

Dr Aonghus McNabola
Trinity College Dublin
Dublin 2
Ireland

Dr Laurence Gill
Trinity College Dublin
Dublin 2
Ireland

Dr Francesco Pilla
Trinity College Dublin
Dublin 2
Ireland

Dr James McGrath
National University of Ireland Galway
Galway
Ireland

Dr Andrew McCreddin
Trinity College Dublin
Dublin 2
Ireland

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Executive Summary

The adverse health effects of air pollution are well established, but previous studies on this topic have generally considered the average pollution concentration in an area rather than the specific concentration experienced by an individual. Variations in the locations (both indoors and outdoors) occupied by individuals and the activities in which they participate lead to variations in their exposure to pollution, in the uptake of air pollutants in their lungs, and in consequent health effects. The development of a methodology for modelling this variation in personal exposure offers a valuable alternative to expensive personal monitoring. The Personal Activity–Location Model (PALM) project investigated methods for modelling an individual's personal exposure to air pollution taking into account variations in their activity and location. The project produced three different models:

1. A statistical model of the personal exposure of individuals in Dublin;
2. An improved version of the Indoor Air Pollutant Passive Exposure Model (IAPPEM); and
3. A set of dispersion models embedded in ArcGIS for ambient air quality in the Dublin area (PALM-GIS).

All of these models are available for further use.

The project included an intensive personal air quality monitoring field study of the variation in exposure to particulate matter experienced by Dublin residents who work in office environments in the city centre. The monitoring campaign collected continuous and consistent information on the concentrations of particulate matter to which subjects were exposed over consecutive 24-h periods using a real-time particulate matter sampling device, Global Positioning System (GPS) tracking equipment, and a personal activity diary. Particulate matter was chosen as the main pollutant to be monitored due to its health significance, its multi-source nature (indoor and outdoor environments), and its suitability for real-time monitoring. The results of this study were used to develop statistical models of personal exposure variation including Generalised Regression Neural Network modelling and Monte Carlo simulation.

The state-of-the-art probabilistic model for indoor exposure, IAPPEM, was developed to include a 1-min time resolution, a variable airflow rate and a modified PM_{10}[1] deposition rate (which accounts for the variability in $PM_{2.5}/PM_{10}$ ratios). This model's ability to perform a detailed analysis of overall particulate matter contribution from multiple different emission sources in a variety of interconnected internal locations in a dwelling was demonstrated by comparing modelled and measured concentrations. Emission source location and internal household configuration were found to have significant effects on pollutant transfer throughout a dwelling. The IAPPEM was found to accurately model the effect on $PM_{2.5}$[2] concentrations of interzonal airflow variations over 10 min or more, with increasing accuracy for longer durations, whereas the use of time-weighted average airflow rates led to the under-prediction of concentrations by up to 28%. Simulations with the IAPPEM found that modelling indoor exposure based on time-averaged profiles is a poor substitute for the use of time–activity profiles which describe how individuals move through different zones in a dwelling.

A geographic information system (GIS)-based air quality modelling framework for the Dublin area was created that integrates a set of air quality models and generates input data to allow exposure modelling to be extended to a wider range of individuals. The synthesis of these modelling tools within a GIS platform provides authorities with a tool to correlate exposure estimates with other thematic layers, such as land use and population density. The principal components of the framework model urban background concentrations, dispersion of road traffic emissions on different road types, and dispersion of pollutants from point and area

1. PM_{10}, particulate matter ≤10 µm.
2. $PM_{2.5}$, particulate matter ≤2.5 µm.

sources. The background model uses artificial neural networks to model the non-linear relation between PM_{10} data recorded at permanent air quality monitoring stations and weather variables recorded at meteorological stations. The integrated model was validated by modelling the personal exposure to particulate matter of the field study subjects while they travelled to work in Dublin City Centre using different routes and different transport modes.

The project has identified the significance of indoor air quality on the overall impact of air pollution on the health of a typical office worker. Exposure and uptake during indoor activities, such as working and cooking, significantly outweighed those identified during outdoor activities, such as commuting. Exposure to and uptake of pollutants must both be considered when comparing health impacts across different activities; the use of concentration exposure alone can result in significant misinterpretation of relative health impacts. Differences between mean personal exposure measurements and background air quality data identified in previous air pollution exposure assessments were confirmed in this study, which has implications for current policy on air quality management and for epidemiological modelling investigations.

1 Introduction

The personal exposure of an individual to air pollution and the associated health impacts are multifaceted and vary with a range of factors. The impacts of meteorological factors and traffic conditions on personal exposure are well documented (Adams et al., 2001), as are the exposure impacts of different activities such as commuting (O'Donoghue et al., 2007), and the health impacts of chronic and acute exposure to particulate matter (PM) (Michaels et al., 2000; Oberdörster, 2000). Since the developed world population spends approximately 90% of its time indoors, personal exposure in indoor environments is especially important, and determinants of personal exposure, such as smoking, have been shown to have a large influence on the personal exposure concentrations of an individual (Koistinen et al., 2001), while the indoor activity of cooking is known to produce an appreciable mass of airborne particles in the vicinity of the cooker (Abdullahi et al., 2013). Previous research has also indicated possible adverse health effects such as cardiovascular disease associated with occupational particulate exposures (Magari et al., 2001; Fang et al., 2010). As such, it is clear that the variety of activities carried out by individuals on a daily basis has an important influence on their personal exposure to air pollutants.

The uptake of pollutants in the lungs is also an important element in the assessment of the health impact of air pollution exposure and an area often neglected by studies of personal exposure to air pollutants. Investigations have shown that the differences in the physiological state (breathing rate, frequency, etc.) of population subgroups can result in differing impacts of air pollutant exposure among such groups. For example, investigations have shown that while exposure of individuals to air pollutants in private vehicles may be typically higher than for cyclists or pedestrians in commuter transport, when breathing parameters and duration of exposure are taken into account, transport modes, such as cycling, often exhibit a higher health impact from air pollution (McNabola et al., 2008).

The monitoring of personal exposure to air pollution incurs considerable costs, in terms of expense, time and resources (Hoek et al., 2002). As a cheaper and more readily available alternative to personal exposure measurements, background air quality measurements are often used to represent the exposure of individuals or groups. This approach has been the basis for a significant body of epidemiological evidence of the health impacts of air pollution (Dockery et al., 1993), and has produced important results in the field of air pollution science.

However, it is also often highlighted that the use of ambient air quality data to represent the personal exposure of individuals has drawbacks (Steinle et al., 2013). Differences between background air quality measurements and individual personal exposure may represent a weakness in current epidemiological models. To improve this situation, without the need for expensive and resource-intensive personal exposure monitoring, reliable and accurate models of personal exposure are required.

1.1 Objectives

The Personal Activity and Location Model (PALM) project aimed to develop a methodology for modelling an individual's personal exposure to air pollution. This methodology should capture the important factors and processes that influence an individual's exposure; in particular it should allow the variations in exposure experienced by individuals performing different activities and in different locations to be evaluated. The resulting model outputs will facilitate individuals in mitigating their personal exposure.

Specifically, the PALM project had the following objectives:

- To experimentally investigate the activities and locations that most contribute to the personal exposure of a class of individual, namely residents of the Greater Dublin Area (GDA) who commute to work in offices in Dublin city centre;

- To develop and evaluate statistical modelling techniques for evaluating personal exposure using field measurement data;
- To develop a model to calculate indoor personal exposure that captures the short-term variations experienced by individuals as they move between compartments and engage in different activities; and
- To develop a model to calculate ambient concentrations at a variety of receptor types in the urban environment of Dublin, taking into account variations in meteorological conditions and proximity to diverse sources of air pollutant emissions.

1.2 Methodology

The PALM project was structured as a set of work packages, each of which addressed one of the objectives listed above. The initial phases of the project designed and executed a field monitoring campaign that collected continuous and consistent information on the concentrations of PM to which a group of individuals was exposed over a number of days, and interrogated these data to identify the activities and locations that make the largest contribution to overall personal exposure. This information was essential for the development of an efficient and effective modelling methodology. Later phases of the work developed independent models for overall personal exposure, indoor personal exposure and outdoor personal exposure, using statistical, probabilistic and deterministic methods, respectively. These methods are described in the following chapters.

2 Personal Exposure Monitoring and Modelling

2.1 Introduction

This part of the PALM project comprised an experimental investigation of the personal exposure of office workers over sequential continuous 24-h periods. An individual's exposure while carrying out different activities in various micro-environments was measured and the associated uptake of pollutants determined. Exposure assessments were performed for subjects distributed throughout the GDA. The obtained results quantify the relative importance of exposure to air pollution in different micro-environments for overall health impact. Personal exposure and pollutant uptake were analysed and compared. The relative importance of activities such as smoking and cooking on personal exposure was highlighted, as was the dominant influence of indoor air quality. A full description of this work is contained in McCreddin (2013).

2.2 Exposure Assessment

2.2.1 Methodology

A 24-h personal exposure monitoring campaign was undertaken over a period of 28 months, from February 2009 to June 2011. A total of 59 volunteer subjects measured their personal exposure to PM_{10}[1] over 255 24-h sampling periods. To reduce variation among the sample population, the recruitment of subjects was restricted to office workers living and working in the GDA and samples were collected during weekdays only. The study population was 57% male and 43% female. Forty-eight per cent of the subjects were aged 26–35 years, with 27% in the 18–25 years category and the remainder between 36 and 55. Approximately 12% of subjects declared themselves to be smokers of some degree, or resided with a smoker.

Sampling of personal exposure, activity and location of subjects was carried out using a real-time PM (PM_{10}) sampling device (Met One Aerocet-531 particle profiler), Global Positioning System (GPS) tracking equipment (Garmin GPSMAP® 60CSx), and a personal activity diary. PM was chosen as the main pollutant to be monitored due to its health significance, its multi-source nature (indoor and outdoor environments), and the ability to record its concentration using real-time monitors that are small and mobile whilst maintaining sufficient resolution and accuracy.

The data set for all 24-h sampling periods collected by the subjects was compiled using the statistical software package SPSS (v16.0). Each sample in the data set comprised the following variables:

- Date;
- Time;
- PM_{10};
- Wind speed;
- Wind direction;
- Temperature;
- Precipitation;
- Sunshine hours;
- Pressure; and
- Relative humidity.

The concentrations of PM_{10} were represented both as overall 24-h daily averages, and by the mean concentrations encountered in each of the main micro-environment/activity categories:

- At work;
- At home;
- Sleeping;
- Shopping;
- Recreation/Sport;
- Commuting;

1. PM_{10}, particulate matter ≤10 µm.

- Café/Restaurant;
- Public house;
- Cooking;
- Other indoor; and
- Other outdoor.

The final two activity categories of 'Other indoor' and 'Other outdoor' are amalgamations of infrequent indoor and outdoor activities, such as visiting a library or a post office. The resulting matrix was subsequently analysed for descriptive statistics and mean comparison tests were carried out to investigate statistically significant (or otherwise) relationships within the data.

The uptake of PM during various activities was estimated in this study using an adaptation of the International Commission on Radiological Protection (ICRP), Human Respiratory Tract (HRT) Model. The model, its adaptation and application are described in full in McNabola et al. (2008) and in ICRP (1994). The model was used to convert personal exposure concentrations (µg/m^3) in each micro-environment to uptake (µg). This was carried out by assigning respiratory rates to the different levels of physical exertion along with information on the time spent in particular micro-environments for each sampling period. The model also took account of variations in uptake according to the subject's gender, age, height and weight.

2.2.2 Results

2.2.2.1 Time–activity budgets

A large amount of activity data was gathered in conjunction with PM_{10} exposure sampling. The activity diary and GPS enabled different activities, as well as micro-environments, to be identified and matched to the data set values obtained from the Aerocet-531 instrument. During the sampling campaign, subjects spent, on average, 92% of their time indoors per day, with a further 3% spent in enclosed transit. The total indoor time percentage can be broken down into four major micro-environments of:

1. At home in a residence;
2. At work;
3. In a café/public house/restaurant; or
4. Some other 'Other indoor' location.

The largest amount of time was spent by subjects in a residence, which represented 59% of their time. Of this time spent at home, the average time spent sleeping was found to be 494 min, while the subjects were classified as 'active' in the home for the other 305 min. Time spent cooking also comprised, on average, 49 min of the time the study population spent in a residence. Outside the home, the sampling population spent most time at work, which represented, on average, 30% of a person's day. Smaller amounts of time were spent in other places such as a café, pub, restaurant, commuting or other indoor locations.

2.2.2.2 Personal exposure

The mean 24-h PM_{10} concentration for the study population was found to be 32 µg/m^3 (σ = 31 µg/m^3). The highest mean 24-h PM_{10} concentration for an individual subject in the data set was recorded as 293 µg/m^3; however, 75% of the daily average data concentrations for subjects were under 36 µg/m^3. Figure 2.1 illustrates a typical 24-h PM_{10} personal exposure time-series history collected during the sampling campaign.

The highest mean PM_{10} concentration during a discrete activity was found to occur during the activity of cooking, for which a mean concentration of 146 µg/m^3 was measured. Cooking events primarily occurred during the evening in a subject's home and typical concentrations varied according to the type of cooking, length of cooking and ventilation conditions in the dwelling. This was followed by the category of 'Other indoor' which had a mean concentration of 67 µg/m^3. However, this category included many activities not repeated on a daily basis by the majority of the subjects, i.e. activities seldom undertaken in comparison with the other clearly defined micro-environments such as at home or at work.

2.2.2.3 Pollutant uptake

The mean 24-h PM_{10} uptake amongst subjects was found to be 425 µg (σ = 347 µg). The uptake for the study population was found to vary considerably

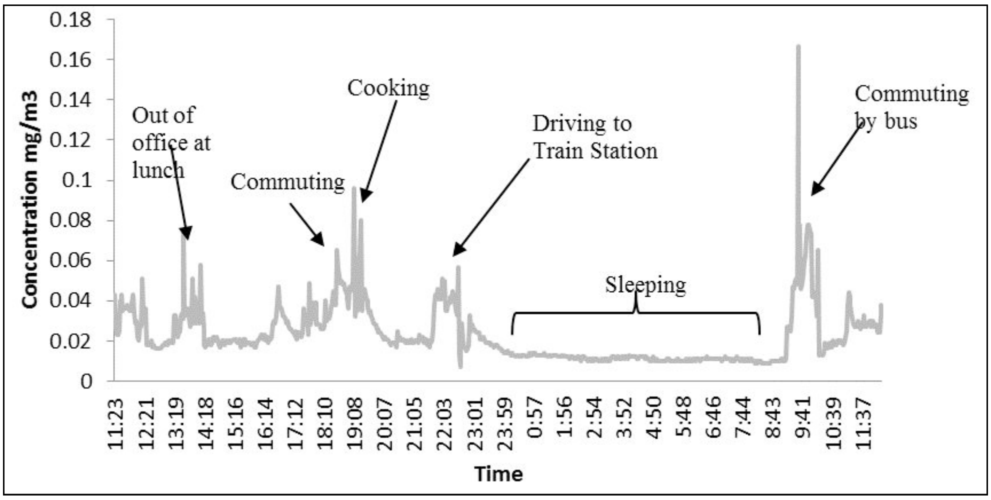

Figure 2.1. Typical 24-h time series profile annotated with the activities carried out.

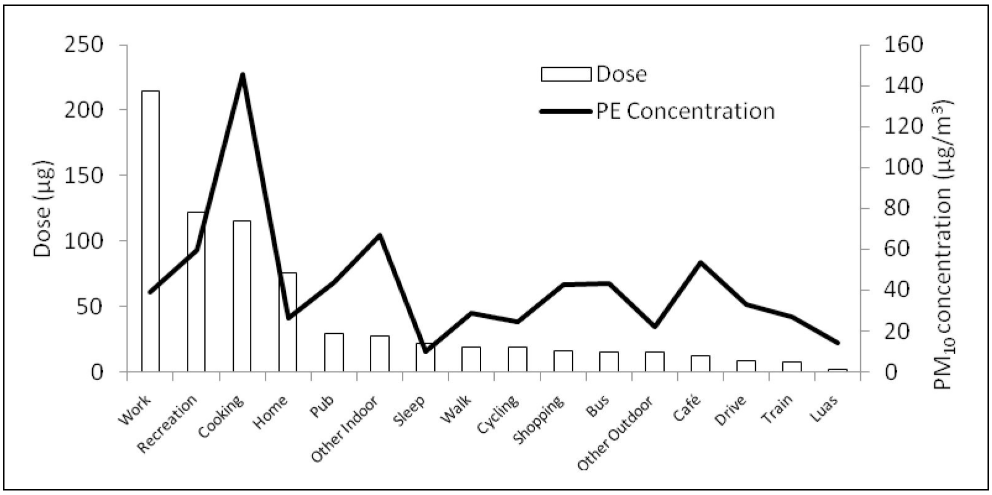

Figure 2.2. Comparison of mean daily uptake and personal PM_{10} concentrations by micro-environment.

across the different micro-environments and activities, and the obtained results demonstrate why subjects experienced higher uptakes in certain micro-environments than in others (see Fig. 2.2).

2.2.3 Discussion

2.2.3.1 Overview of personal exposure and pollutant uptake

Personal exposure studies of PM_{10} and $PM_{2.5}$[2] in a number of other cities have found much higher personal concentrations (Branis and Kolomazníková, 2010; Borgini et al., 2011), but these studies were conducted in regions with higher ambient concentrations of PM generally. The average ambient outdoor PM_{10} concentration measured at a fixed site monitor in Dublin City during the sampling campaign was just 13 µg/m^3, which can be compared with the mean 24-h concentration experienced by the study population of 32 µg/m^3.

The largest uptake of PM_{10} among subjects was found to be in the office working environment, which had a mean uptake of 214.2 µg. This was followed by recreation or sport (122.0 µg) and cooking (115.2 µg). The mean uptake while active at home was 75.9 µg, falling to 22.9 µg while sleeping. The commuting modes of subjects were observed to have some of the lowest mean uptake of all micro-environments.

2. $PM_{2.5}$, particulate matter ≤2.5 µm.

Exposure and uptake of pollutants in the workplace were a common factor in all samples and clearly a key area through which improvements in health impact could be achieved using control measures. Sport and recreation activities were less common among the study population but were nonetheless notably elevated in terms of both exposure and uptake, especially when carried out indoors.

While cooking activities were not universally performed by subjects, with approximately 50% of sampling days including one or more cooking event, as the third highest source of pollutant uptake, it was a key determinant in overall exposure and uptake of PM_{10}. A number of cooking events resulted in very high measured concentrations, which were dependent on the form and duration of cooking, as well as on ventilation conditions. However, it was impractical to accurately determine the ventilation parameters for each cooking event during this study, and it was also difficult to separate the impact of differing types of cooking as these were often carried out concurrently (e.g. boiling and frying together). Increased awareness among the public of the health benefits of adequate ventilation during cooking could reduce this component of exposure.

Subjects spent the majority of their time indoors, predominantly in their residence, where two-thirds of their time was spent sleeping, and one-third spent active in the home. The activity of sleeping had a relatively low mean personal exposure concentration (10 µg/m^3) due to the lack of activity in the residence at those times. In contrast, the personal concentrations measured when each subject was active at home were far greater. In addition to the home micro-environment, 30% of each subject's day was spent at work. Other micro-environments such as commuting, shopping and recreation accounted for only small portions of the daily routine of the study population. As the mean occupational personal exposure (39 µg/m^3) of the office workers in this study was found to be higher than their overall 24-h mean personal exposure, this micro-environment played a key role in the day-to-day personal exposure concentrations of individuals.

These findings highlight the importance of indoor air quality on the overall impact of air pollution on the health of a typical office worker. Office workers in this study lived predominantly outside of the city centre and worked in offices located in the city centre. This was reflected in the in-home concentrations being typically lower than those at work. The control of air pollution in the workplace in Ireland has seen some improvement in recent years with the introduction of the ban on smoking for example. This was evident in the elevated in-home concentrations measured in the houses of smokers (including during the activity of sleeping) compared with their workplace exposure concentrations.

2.2.3.2 Transport micro-environments and commuting

The highest PM_{10} concentrations were found while travelling by bus (43 µg/m^3), whereas travel by tram displayed the lowest personal exposure (14 µg/m^3). Significant research efforts have focused on personal exposure in the transport micro-environment, particularly during commuting. However, in this study, exposure during transport activities was found to be insignificant in comparison with the contribution of indoor air quality in the workplace and at home to overall daily exposure. Michaels and Kleinman (2000) highlighted the significance of brief excursions in micro-environments with high 1-h peak concentrations of PM on the health of humans. In this study, these conditions were predominantly observed in the home and were associated with cooking or smoking rather than in outdoor transport micro-environments.

This does not suggest that transport emissions in Dublin had little impact on the environment or the public, as previous investigations have shown that 50–80% of particulate air pollution in buildings originated from external sources (Hsu et al., 2012). Sources of indoor particulate air pollution in Irish homes are investigated in Chapter 3.

2.2.3.3 Comparison of personal exposure and uptake

The activity category of 'Other indoor' was found to have a relatively high mean PM_{10} concentration (67 µg/m^3) during the measurement campaign. However, due to the relatively infrequent and short amount of time spent in some of these micro-environments, the actual population uptake over 24 h was low (27.8 µg). A similar situation was observed with cafés and restaurants, and the impact of the highest exposure category, cooking, was reduced when breathing rates and exposure duration were considered.

The pollutant uptake by subjects at work and active at home were, as expected, both large contributors to total 24-h total uptake. However, higher activity levels while at work (40% sitting and 60% light exercise) led to this activity making by far the greater contribution. The average uptake while at work (214.2 µg) was nearly three times that in the home (75.9 µg) even though there was only a 49% difference between the mean exposure concentrations measured for the two activities.

2.3 Statistical Personal Exposure Modelling

2.3.1 *Introduction*

There are a variety of approaches to the modelling of personal exposure to air pollution. These include the use of time-integrated activity modelling, where the total 24-h personal exposure is modelled as the sum of a series of values evaluated as the product of time spent in a micro-environment and the corresponding pollutant concentration in that micro-environment. Statistical techniques, such as the use of Artificial Neural Networks (ANNs), have also been used to predict personal exposure based on the analysis of historic data records.

The PALM project investigated alternative methods of personal exposure modelling that made direct use of the measured personal exposure data described above. The performances of three personal exposure modelling techniques were compared:

1. Time-integrated activity modelling;
2. Monte Carlo simulation; and
3. Neural network modelling.

2.3.2 *Methodology*

The development and formulation of each investigated model is described in full in McCreddin (2013). The performances of the models were validated by dividing the data set of personal exposure measurements into model development and model validation data sets. The model development data set consisted of 230 24-h samples, which represented 90% of the overall data set, while the validation data set consisted of the remaining 10%. The validation data were chosen from the main data set using a specially developed algorithm implemented in MATLAB that randomly chose and removed 25 sampling days from the main data set and stored them in a separate file for later model testing.

2.3.3 *Results and discussion*

Table 2.1 provides a summary comparison of the performance of the different models. A more detailed discussion of model performance and accuracy is presented in McCreddin (2013). As a general observation it is clear that all models displayed reasonably good predictive performance, with the Pearson’s correlation coefficients in the region of 0.55–0.84 and the normalised mean bias (NMB) values generally less than 10%. Some differences in performance did exist and clearly Model 3 using the

Table 2.1. Comparison of model performance – Pearson’s correlation coefficient (r), root mean square error (RMSE) and normalised mean bias (NMB) (McCreddin, 2013).

Model	Model basis	r	RMSE ($\mu g/m^3$)	NMB (%)
1	Time weighted	0.55	10.2	9.3
2	Time weighted	0.55	11.7	10.2
3	Monte Carlo	0.59	9.8	6.6
4	FFNN	0.84	26.5	–17.2
5	GRNN	0.77	11.8	–6.6

FFNN, Feed Forward Neural Network; GRNN, Generalised Regression Neural Network

Monte Carlo simulation of micro-environmental exposure distributions resulted in the most accurate predictions, considering all three performance criteria. However, the differences in performance could be said to be minor and perhaps a more important aspect of the critical examination of the approaches is the utility of each modelling approach as a means of evaluating personal exposure for epidemiological investigations.

Time-weighted activity models have been the subject of numerous investigations but, of the five techniques examined here, this approach produced some of the poorest model performance statistics. Moreover, this methodology has a lower utility than the other approaches, in that it is heavily dependent on the availability of measured data and is less readily transferable to different locations or subject types as a significant amount of measured personal exposure data is required to develop a location/subject-specific model. In comparison, the Monte Carlo simulation technique offers a potentially higher degree of transferability to other locations and subject types.

Model 3 was a variation on the time-weighted activity approach and employed a format similar to that laid out in the EXPOLIS study (Jantunen et al., 1999). The potential higher utility of Model 3 in comparison with the traditional time-weighted activity techniques lies in the transfer of statistical distributions of micro-environmental exposure concentrations from one location to another. For example, it may be reasonable to assume that as the personal exposure to PM_{10} in the homes of 59 office workers in the GDA was observed to follow a log–log distribution, this distribution also applies to the homes of individuals in locations outside of Dublin, and to the homes of other population groups. While the mean concentrations in homes may vary by location and socio-economic grouping, the question highlighted in this research is whether a single observed statistical distribution is applicable to a large number of homes or home types? Confidence in the statistical distribution of air pollution concentrations in different micro-environments, together with a limited amount of data on mean exposure concentration, would facilitate the extension of this modelling technique to numerous locations and sectors. A probabilistic method of indoor air quality modelling that employs such distributions is presented in Chapter 3.

Aside from its potential in transferability, Model 3 also showed somewhat stronger predictive performance than any of the other four modelling approaches. The key difference in Models 1 to 3 lies in the selection of concentrations to represent different mean micro-environmental exposures. Model 1 was based on the population average and is, as such, clearly a very static model where predictions will change only as a result of time–activity patterns. Model 2 was based on average exposure of a specific subject in a particular micro-environment which again results in a very static model with limited transferability. The improved performance of Model 3 clearly lies in the random variation of the micro-environmental concentrations according to a statistical distribution. Such variation results in a more dynamic model, which caters for the variable nature of personal air pollution exposure.

The ANN modelling approach produced impressive results when using a Generalised Regression Neural Network (GRNN), but not when using a Feed Forward Neural Network (FFNN). In comparison with the Monte Carlo simulation approach, the GRNN model produced a higher Pearson's correlation coefficient, a lower root mean square error (RMSE) and a very similar NMB. However, this technique is heavily dependent on the availability of a significant amount of training data to develop the model, and is consequently not readily transferable to other locations or other population sub-groups.

2.3.4 Observations

The cost of personal exposure measurements presents a barrier to their inclusion in air pollution health impact assessment and thus readily available background air quality data are often used in their place. Personal exposure models, which themselves also require a significant amount of measurement data for their development and offer limited scope for transferability to differing locations or differing population groups, do not provide a solution to this problem. However in addition to its strong ability to predict personal exposure among office workers in this study, it was concluded that the Monte Carlo simulation technique offers potential scope for improved transferability, with limited measurement data requirements. However, the extent of this transferability remains to be determined.

3 Indoor Air Quality Modelling

3.1 Background and Identification of Knowledge Gap

The use of computational models in predicting exposure to gaseous or particulate indoor air pollutants has been well documented. It is often expensive or impractical to obtain direct indoor measurements (or personal exposure measurements) for large population groups in epidemiological studies, and computational models are a recognised substitute. Computational modelling of indoor air quality has the benefits of cheaply and easily evaluating population exposure and potential mitigation through changes in either building-design-related strategies or behavioural strategies. Models are also effective tools for separating the contributions from indoor and outdoor air pollution sources, allowing effective exposure reduction strategies to be devised.

Prior to conducting the model development research described below, a review of the literature was conducted to establish the status of current technology in indoor air quality modelling (McGrath, 2014). CONTAM (NIST, Gaitherburg, MD, USA) is a multi-zone, airflow and transport pollutant model considering airflow paths, ventilation system and emission sources (NIST, 2011). To date, CONTAM has been used in over 54 published applications, making it the most widely used indoor air pollutant model. Fabian et al. (2012) used CONTAM to predict nitrogen dioxide (NO_2) and PM_{10} concentrations in low-income family homes in Boston, for use in a health-based intervention study, which highlighted the challenges imposed on simulations due to the large variation in emission strengths. Being a deterministic model, CONTAM is unable to consider variations in modelling parameters, limiting its use in complex indoor environments as every input parameter has an associated level of uncertainty.

Due to the existence of large uncertainties surrounding the parameterisation of exposure models, probabilistic approaches such as that employed by the INDAIR model (described below) are necessary, but this type of model has had limited development to date. Probabilistic models, by employing probability density functions, simulate a range of possible values for each input parameter, overcoming some of the uncertainties in experimentally obtained data, but can also encompass uncertainties in the selection of appropriate modelling parameters between studies. While current models have demonstrated the capability to predict indoor PM_{10} and $PM_{2.5}$ concentrations, the need still exists for a comprehensive probabilistic model capable of simulating more realistic representations of a home environment. Such a model should encompass the full range of possible emission sources located in different room types and, simulated on a sufficiently short timescale, capture details in peak and mean concentrations and accurately determine the time duration for emission concentrations to fully decay.

In this part of the PALM project, an existing probabilistic model, INDAIR, was developed into a state-of-the-art model, Indoor Air Pollutant Passive Exposure Model (IAPPEM). The IAPPEM's ability to fully assess the distribution of particulate air pollutants in dwellings is demonstrated through analysis of model results from a wide range of simulations.

3.2 Model Development

The INDAIR model provided an internationally advanced probabilistic modelling tool to assess the contribution of indoor and outdoor sources to pollutant concentrations in the indoor environment. It could simulate the upper percentiles of the population exposure to air pollutants, or the proportion of the population exposed to concentrations above critical health thresholds. However, the INDAIR model still possesses a number of limitations that prevent its full application to representative indoor environments. The review of the literature highlighted the large variation in emission rates, deposition rates and air exchange rates that are possible, and, while the probabilistic approach accounts for these, the temporal and spatial limit restrictions of INDAIR restrict its scope. The

IAPPEM redresses these deficits by making a number of significant adaptations to INDAIR; the benefits offered by each adaptation in improving personal exposure assessment are summarised below:

- In contrast to INDAIR, which employs a simplistic three room layout of the home environment, the PALM project developed the spatial model into 15 interconnecting rooms which can be combined to represent different household layouts. This allows the examination of the impact of source location and household layout on indoor concentrations, while predicting exposure for multiple individuals present in the same dwelling. The model determines the rooms containing the lowest concentrations and this information can be used to develop strategies to help reduce exposure.

- The temporal resolution of the model was improved from 15 min to 1 min. It was found that simulations carried out at this increased resolution showed improved predictions of peak PM concentrations. While no substantial difference in 24-h mean concentrations was observed, this was not the case for the 24-h mean exposure. Short-term peaks in concentrations can have a considerably greater impact on mean exposure than on mean concentrations; an individual moving through a series of micro-environments can be exposed to multiple peaks in different micro-environments, although each peak might only occur once in each micro-environment.

- An adapted PM_{10} deposition term was included (Fig. 3.1), which is especially important when multiple indoor emission sources are modelled. $PM_{2.5}$ to PM_{10} ratios vary for both outdoor PM concentrations and indoor PM emission sources. Failure to separate the $PM_{2.5}$ and PM_{10} contributions results in the $PM_{2.5}$ contribution being assumed to decay at a rate calculated for the PM_{10} deposition velocity, hence overestimating PM_{10} decay. However, separating $PM_{2.5}$ from PM_{10} results in the prediction of higher PM_{10} concentrations for longer durations. In a simulation, this results in greater PM_{10} transfer throughout a dwelling and higher exposure.

- The improved temporal resolution of the model facilitates short-term variation of model parameters. Simulations using a time-varying airflow rather than a time-weighted average airflow (Fig. 3.2) show that both the peak and the mean concentrations in adjoining rooms are potentially underestimated in the latter case, especially when emission sources are present. The greatest discrepancies occur in peak concentrations, which has implications for evaluations of an individual's personal exposure. This is a significant finding, as short-term

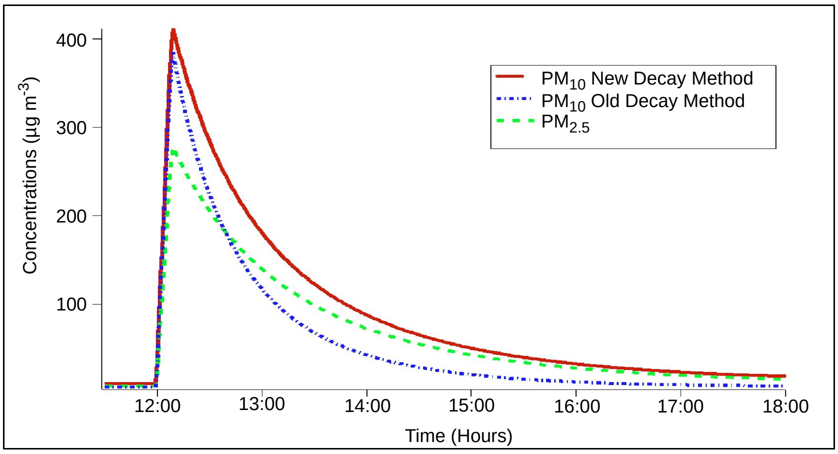

Figure 3.1. Differences in PM_{10} concentrations estimated using the modified PM_{10} decay method, the original PM_{10} decay method and the corresponding $PM_{2.5}$ concentration during a smoking event in the kitchen when doors are closed.

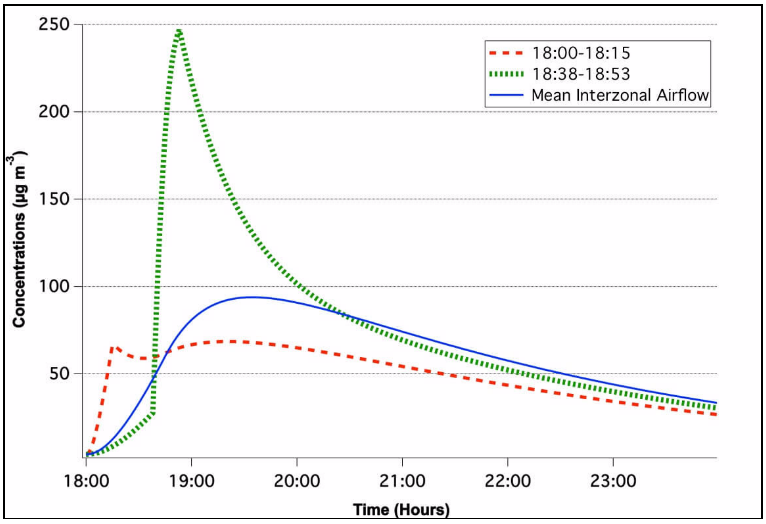

Figure 3.2. $PM_{2.5}$ concentrations in the hall of a house for three different simulations, two with variation in inter-zonal airflow at different time intervals and one using time-weighted average airflow.

fluctuations in concentrations can account for a large exposure variation between population groups. Simulations were based on a time-weighted averaged airflow with a variable airflow, simulating airflow variations by the opening and closing of internal doors. The simulations are validated based on an experimental comparison: examining airflow variations at 1, 2, 5 10, 15 and 30-min intervals.

- The inclusion of multiple emission sources improves the ability of the model to simulate real-life scenarios; in most households, multiple emissions sources are present. Peak and mean PM indoor concentrations vary depending upon the emission source, emission duration and the source's location.

- The INDAIR model had only three additional micro-environments:

  (i) Outdoors;

  (ii) Shop, restaurants; and

  (iii) Transport.

  Within these micro-environments, PM concentrations were calculated based on indoor/outdoor ratios. The IAPPEM can be used to conduct simulations in a total of 10 micro-environments (in addition to the home micro-environment), with the full functionality of the home environment. The micro-environments included are the classroom, office, supermarket, gym, car, tram, train, bus, outdoors, restaurant and a pub. The model has a flexible format that does not limit alternative parameterisation being applied for the simulation of different micro-environments. These additional micro-environments, although not demonstrated in this work, are required to evaluate individual exposure over a 24-h profile.

In summary, the adaptations to the original INDAIR model from which the IAPPEM was developed include an increase in temporal resolution to 1 min, the incorporation of 12 simultaneously operating emission sources, and up to 15 interconnecting rooms. Additionally, the model, which originally calculated airflow on a time-weighted average basis, was adapted to include a variable airflow rate, and the results of simulations demonstrate that, without this feature, $PM_{2.5}$ concentrations may be underestimated by up to 28%. Further, a modified PM_{10} deposition rate, which accounts for variations in $PM_{2.5}$ to PM_{10} ratios, was incorporated into the IAPPEM, with simulations showing that this led to predictions of mean concentrations that were up to 58% higher than those calculated using the unmodified model. Simulations carried out with a 1-min time resolution compared with a 15-min time resolution resulted in the estimation of peak PM concentrations that were 20% higher.

3.3 Demonstration Simulations

Simulations were performed to highlight the contributions of outdoor PM concentrations and indoor emission sources, as well as to demonstrate the combination effect of multiple indoor emission sources (Figs 3.3 and 3.4). Using the IAPPEM, a detailed analysis of overall PM contribution from multiple different emission sources, in a variety of different internal locations in a dwelling, has been carried out for the first time, and the effects of emission source location, emission source timing (Fig. 3.5) and internal household configuration on PM transfer throughout a dwelling have been quantified.

The IAPPEM combines a time–activity model (which describes how individuals move through different zones in a dwelling) with the physical pollutant model, to create a personal air pollutant exposure model. The results of the simulations conducted with this combined model (Fig. 3.6) found that calculations of exposure based on time-averaged profiles are inferior to calculations of exposure based on time–activity profiles. In each simulated scenario, the time-averaged

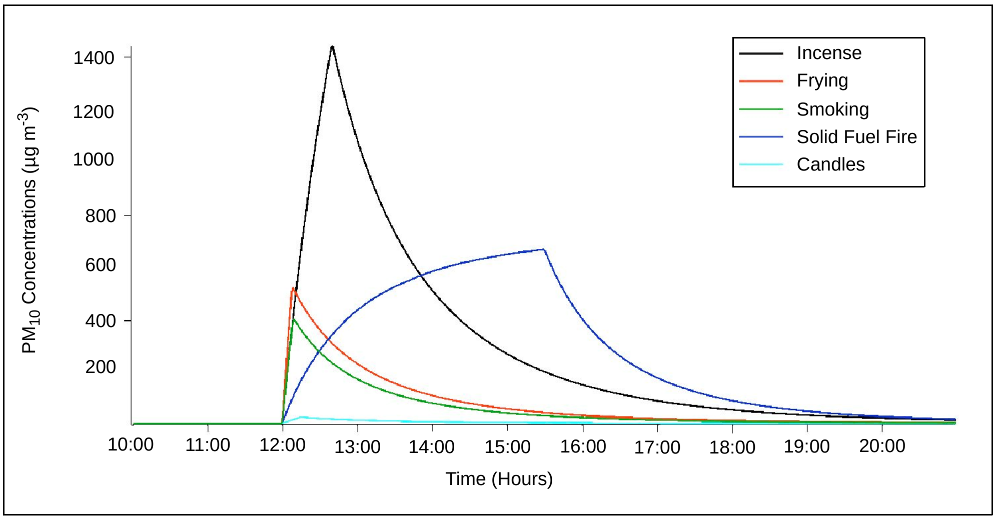

Figure 3.3. Modelled temporal variation of indoor PM_{10} concentrations due to separate discrete emission events from five different source types.

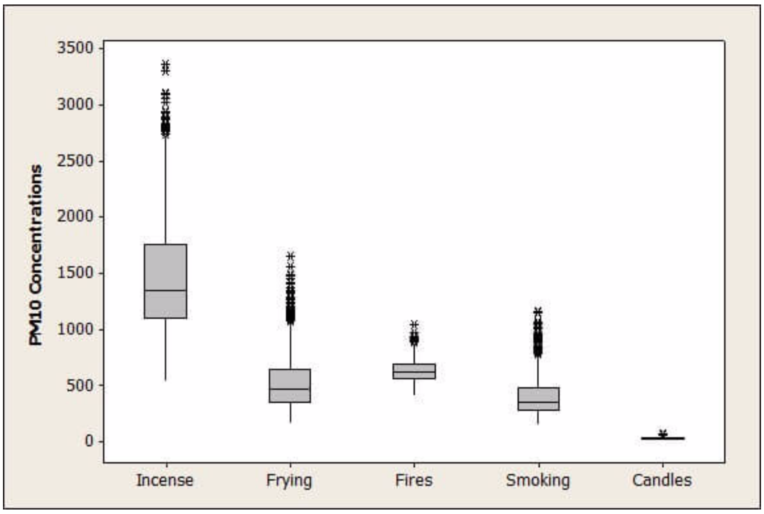

Figure 3.4. Box plot showing the range of modelled peak PM_{10} concentrations (µg/m^3) in the kitchen (with doors closed) for five indoor emission sources.

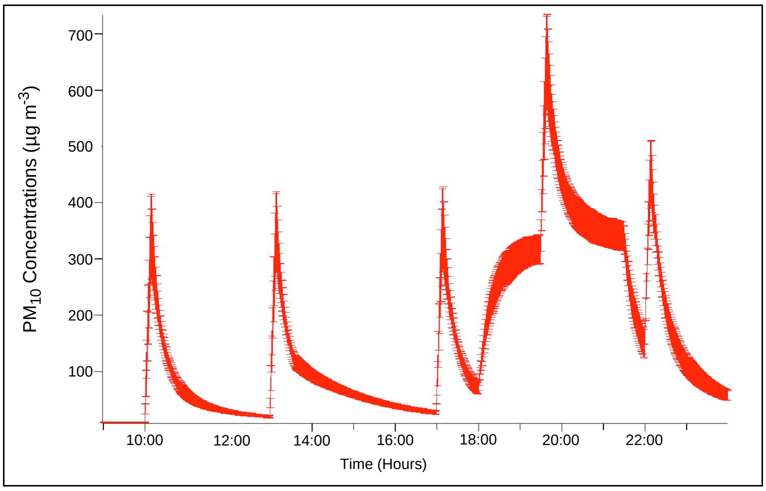

Figure 3.5. PM$_{10}$ concentrations in the living room. The time axis has been scaled to focus on the emission period. The y-bars represent one standard deviation at each time step, highlighting the probabilistic nature of the model. Each of the five peak concentrations refers to the end of a smoking event.

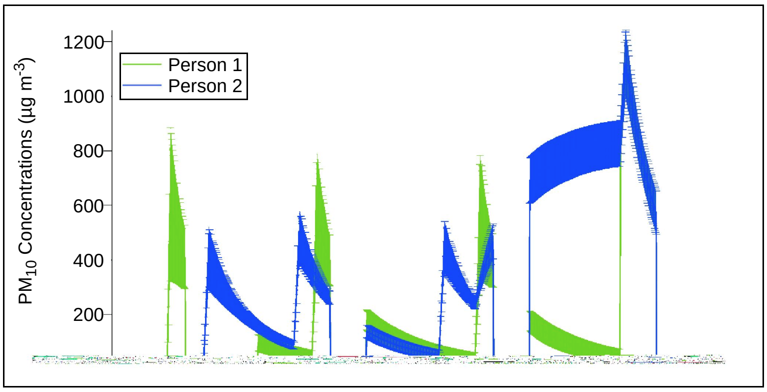

Figure 3.6. Comparison of the personal exposure to PM$_{10}$ of two individuals as they move through different rooms in a dwelling with open internal doors; the probabilistic nature of the model, which defines a value range for each parameter value, is demonstrated.

approach underpredicted mean exposure, in some cases by up to 75%. Additionally, the time-averaged approach failed to provide any information on peak exposure, whereas the time–activity profile approach provided key information on this aspect.

3.4 Validations

A number of experimental validations were carried out by monitoring simultaneous indoor and outdoor concentrations of PM$_{10}$ and PM$_{2.5}$, using a SidePak Personal Aerosol Monitor Model AM510 (TSI Inc., Shoreview, MN, USA). Experimental validations were gathered from a range of different households, examining external and inter-zonal airflow, solid-fuel-fire burning events and indoor emission sources. The validation studies are detailed in pages 118–136 of McGrath (2014). Figures 3.7–3.9 compare the variations in experimental and modelled concentrations during three different emission scenarios.

Table 3.1, taken from McGrath et al. (2014a), presents a comparison of experimental and simulated concentrations for a range of emission source types. The experimental uncertainty on the measured data represents ±1 µg/m^3. Table 3.2, taken from McGrath et al. (2014b), presents a statistical comparison of modelled and measured concentrations in the hall of a

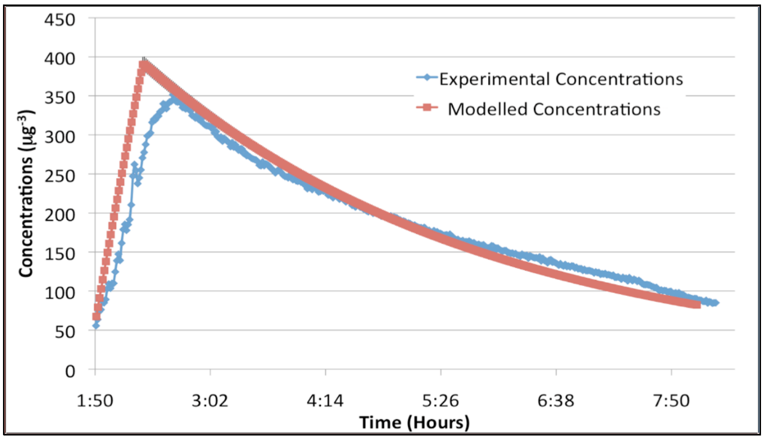

Figure 3.7. Simulation of burning an incense stick for 6 h, to examine the decay period. Predicted $PM_{2.5}$ concentrations are compared with indoor $PM_{2.5}$ concentrations.

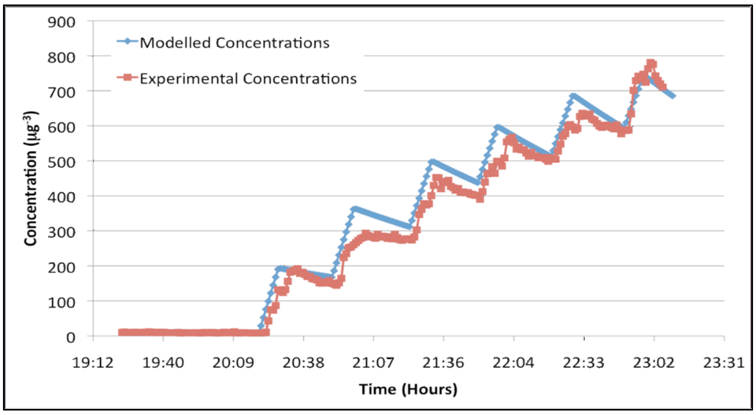

Figure 3.8. A simulation examining multiple smoking events. A cigarette was smoked every 30 min. Predicted $PM_{2.5}$ concentrations are compared with measured $PM_{2.5}$ concentrations.

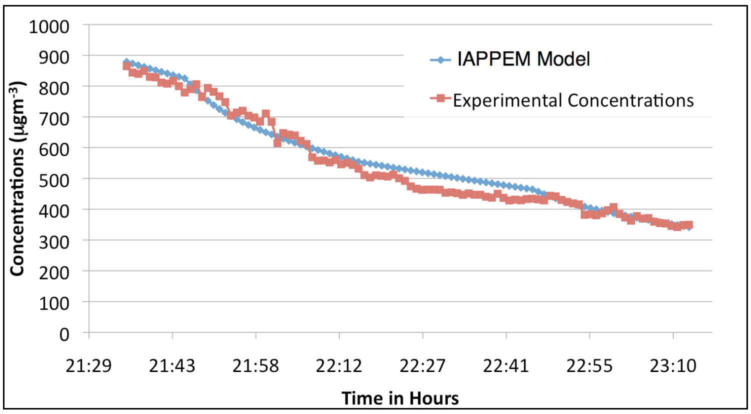

Figure 3.9. Observed comparison between modelled and experimental concentrations in the sitting room when the door is closed; PM concentration decay occurs due to deposition and external airflow.

Table 3.1: Measured and modelled $PM_{2.5}$ concentrations for a range of source types (McGrath et al., 2014a).

Emission scenario	$PM_{2.5}$ concentrations	
	Measured ($\mu g/m^3$)	Modelled ($\mu g/m^3$)
Peak concentrations		
A single cigarette	181	167 ± 14
A frying event	418	398 ± 62
Incense stick	593	633 ± 70
Mean concentrations		
No emission source (2-h mean)	7.3	6.5 ± 1.8
Smoking six cigarettes (4-h mean)	296	294 ± 14
A frying event (2-h mean)	289	276 ± 43
Incense stick (6-h mean)	326	331 ± 41

Table 3.2. Statistical comparisons of experimental and predicted concentrations in the hall of a domestic dwelling (McGrath et al., 2014b).

Scenario	Linear regression	R^2	Experimental peak ($\mu g/m^3$)	Predicted peak ($\mu g/m^3$)
1 min	1.72	0.65	262	149
2 min	0.72	0.41	166	183
5 min	1.11	0.75	159	214
10 min	1.07	0.95	317	280
15 min	1.05	0.64	240	230
30 min	1.02	0.94	489	473

domestic dwelling. Close agreement is observed between the measured and modelled parameters.

3.4 Summary

A state-of-the-art probabilistic indoor air pollution modelling tool has been developed that is superior to others in respect of its capability for considering multiple emission sources in multiple rooms of a dwelling at a greater time resolution than was previously possible. Both air pollution concentration and air pollution exposure values can be calculated, the former directly from the physical model, and the latter by combining the physical model with a time–activity model. Validation and demonstrations have been carried out for PM in the domestic environment but, with appropriate parameterisation, the model can easily be adapted to consider air pollution concentrations of both a particulate and gaseous nature (and additionally, air pollution exposure), in other environments such as workplaces, vehicles and schools.

4 Urban Air Quality Modelling

4.1 Introduction

The use of mathematical models to assess ambient air quality in cities is attractive because of the inherent difficulties and costs involved in monitoring air pollution on numerous streets within an urban area. Such models have been widely adopted by local authorities to assess and quantify population exposure to air pollutants and compliance with regulations (Vardoulakis et al., 2005), and they are, de facto, an essential tool to assess the possible impact of planned developments (Manning et al., 2000). However, modelling the dispersion of air pollutants in cities is not a trivial task as urban areas are not homogeneous entities; the highest levels of pollution often occur in street canyons where pollutant dilution is limited by the presence of buildings flanking the street (Berkowicz et al., 1997).

Epidemiological studies (Vardoulakis et al., 2002) of urban populations have raised concerns over the adverse effects on human health of airborne traffic-related PM, and compelled various agencies to propose more stringent air quality standards (e.g. European Union Council Directive 1999/30/EC; Harrison et al., 2001). Exposure assessment is an integrated part of health risk assessment and management at national, regional and local scales but currently no Irish exposure models exist to support such assessments.

Living or attending school near major roadways has been associated with numerous health outcomes in recent years, including asthma exacerbation (Gordian et al., 2005) and other respiratory illnesses (Brauer et al., 2002). While this growing observational literature has been interpretable and robust, with relative risks that indicate a large public health impact, simulation studies (Baxter et al., 2009) have shown significant exposure misclassification associated with the use of proximity measures relative to 'gold standard' air pollution exposure estimates. While these studies and related work have provided insight about exposure patterns and health effects, and can also characterise air pollution hot spots for public health interventions, significant limitations remain. The above-mentioned studies leveraged temporally rich and spatially dense monitoring data, yet lacked sufficient spatial resolution to capture micro-scale concentration patterns.

The aim of the urban air quality modelling research performed in the PALM project was to obtain a spatio-temporally detailed estimation of air quality in Dublin and of the city inhabitants' individual air pollution exposure through high-resolution modelling. The specific goal was to create a set of integrated GIS-based exposure assessment tools using monitoring data, spatial analysis, stochastic modelling and deterministic modelling to account for the impact of different emission sources and weather conditions on total PM_{10} concentrations. The synthesis of these techniques represents a valuable resource for the assessment of health impacts, and in the development of wider exposure reduction strategies. The presented work also seeks to establish a methodology to support air pollution exposure-response assessments in Ireland. It is also designed to lead to improved air quality action plans, leading to improved environmental awareness amongst the general public and local authorities alike. Furthermore, the research yielded a reliable framework within which epidemiological studies may be performed in the future; thus the impact of the proposed research may extend beyond air pollution in the assessment of other environmental pollutants.

Geographic Information Systems (Wong and Wu, 1996) were identified as an ideal platform for this study because they are extensively used by governments, research centres, environmental agencies and conservation organisations, amongst others. In particular, the Economic and Social Research Institute (ESRI) ArcGIS selected for this work is widely used and comprises a suitable collection of tools that capture, store, analyse, manage, and present data that are linked to geographical locations (Bhat et al., 2011).

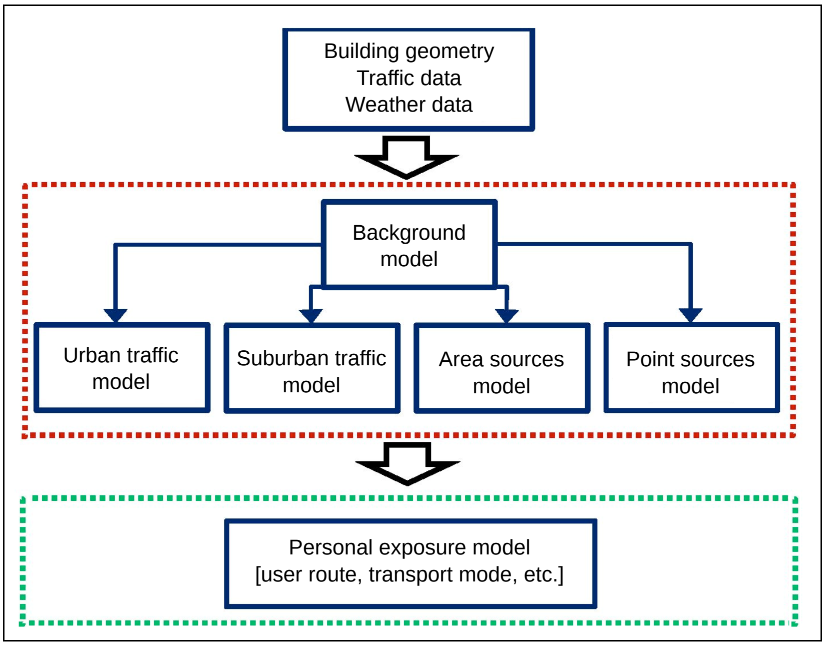

Figure 4.1. PALM-GIS personal exposure model flow chart.

Within the PALM project, air quality models of PM concentrations at various scales, and models of personal exposure to PM are integrated within the ESRI ArcGIS. A conceptual diagram of the resulting PALM-GIS exposure model is presented in Fig. 4.1.

4.2 Model Definition

The sparse permanent air quality monitoring stations around the Dublin area (Fig. 4.2) are not believed to be able to produce a sufficient spatial resolution for the

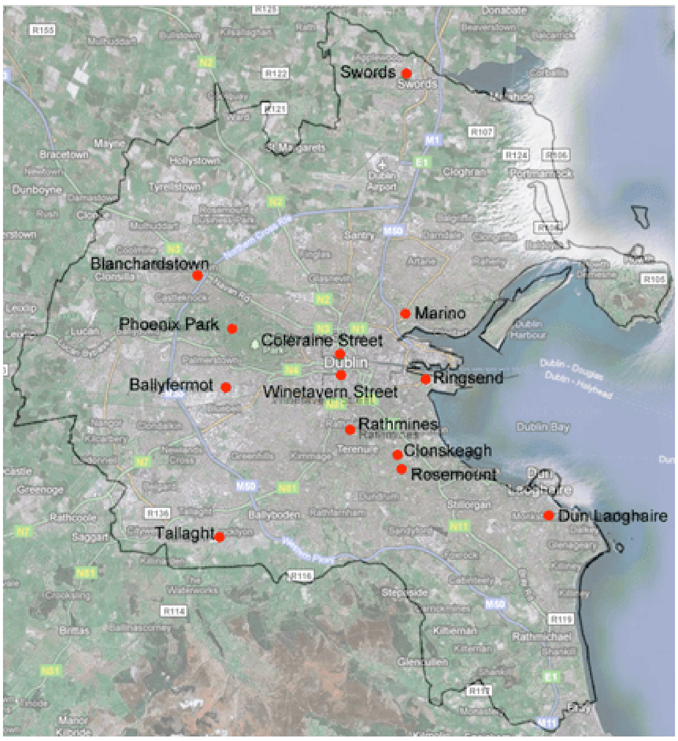

Figure 4.2. Air quality monitoring stations, Dublin area.

pollutant levels: the data collected by these monitoring stations are not representative of the variety of pollutant concentrations existing at individual street level. This detail is crucial when accurate information on the exposure of individuals is required as scientific studies on the health impacts of air quality need to pair estimates of individual exposure to air pollution with the assessment of individual health outcomes. This section describes the creation of an air quality model for the GDA.

A graphic representation of the spatial variation of the different air pollution components that contribute to pollutant concentrations at street level is presented in Fig. 4.3(b). The final street level concentration results from the sum of the following elements:

- Urban background concentrations, sum of the regional background and the urban increment;
- Contribution from important point and area sources; and
- Contribution from traffic.

These three elements are modelled separately and then the corresponding concentrations summed to obtain the total pollutant concentration at street level (Fig. 4.3(b)). For the personal air pollution exposure model developed within the PALM project, the sum presented in Fig. 4.3(b) is performed and displayed using ArcGIS by assigning each component to a different layer. All the tools (developed, freeware and proprietary) are compatible with a GIS platform (tested on ArcGIS 10.1) and available for use. The modelling process for each component is briefly described in the following sections.

4.2.1 Urban background concentrations

The urban background air pollution concentrations are constituted by the sum of the background concentrations and the distributed contributions from the city itself. The background model is generated using data mining techniques using historical PM_{10} data measured by permanent air quality monitoring stations in the GDA and a set of weather variables recorded at Met Éireann weather stations. The air quality stations categorised as 'urban background' using the criteria proposed by the European Environment Agency (Van Dingenen et al., 2004) are employed for this task. A neural network modelling approach is adopted, which is able to recognise patterns between historical air pollution data and causative weather data; the developed relation is then used in combination with forecasted weather data to model and predict the required urban background concentration levels. These results are imported into ArcGIS for visualisation (Fig. 4.4) and combination with the other components of street-level pollution.

4.2.2 Contribution from important point and area sources

Power stations and industrial plants in the GDA are identified along with their emission rates and

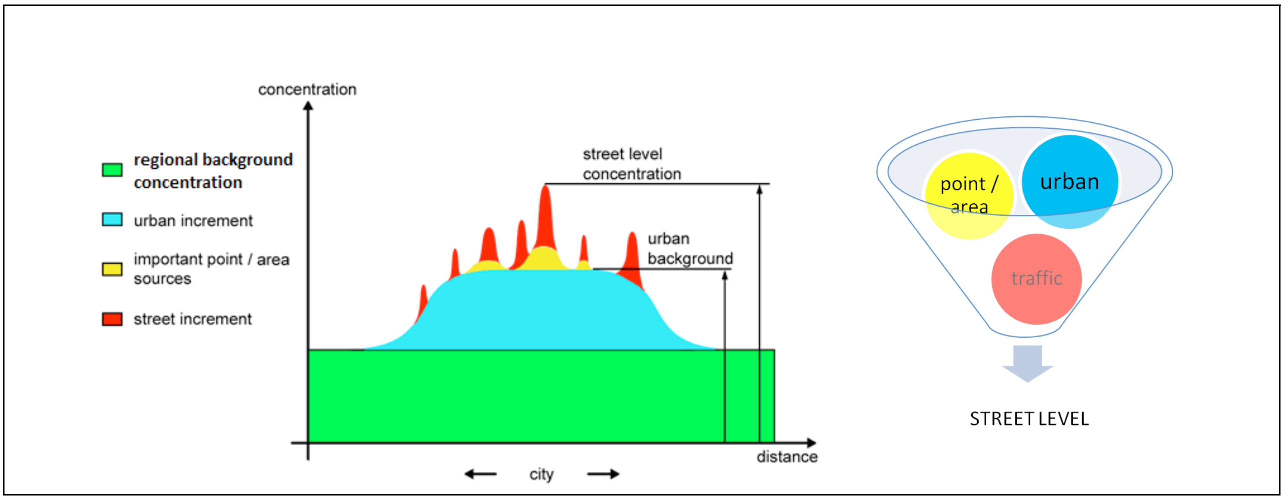

Figure 4.3. (a) Spatial variation of urban air pollution components, and (b) urban air quality modelling.

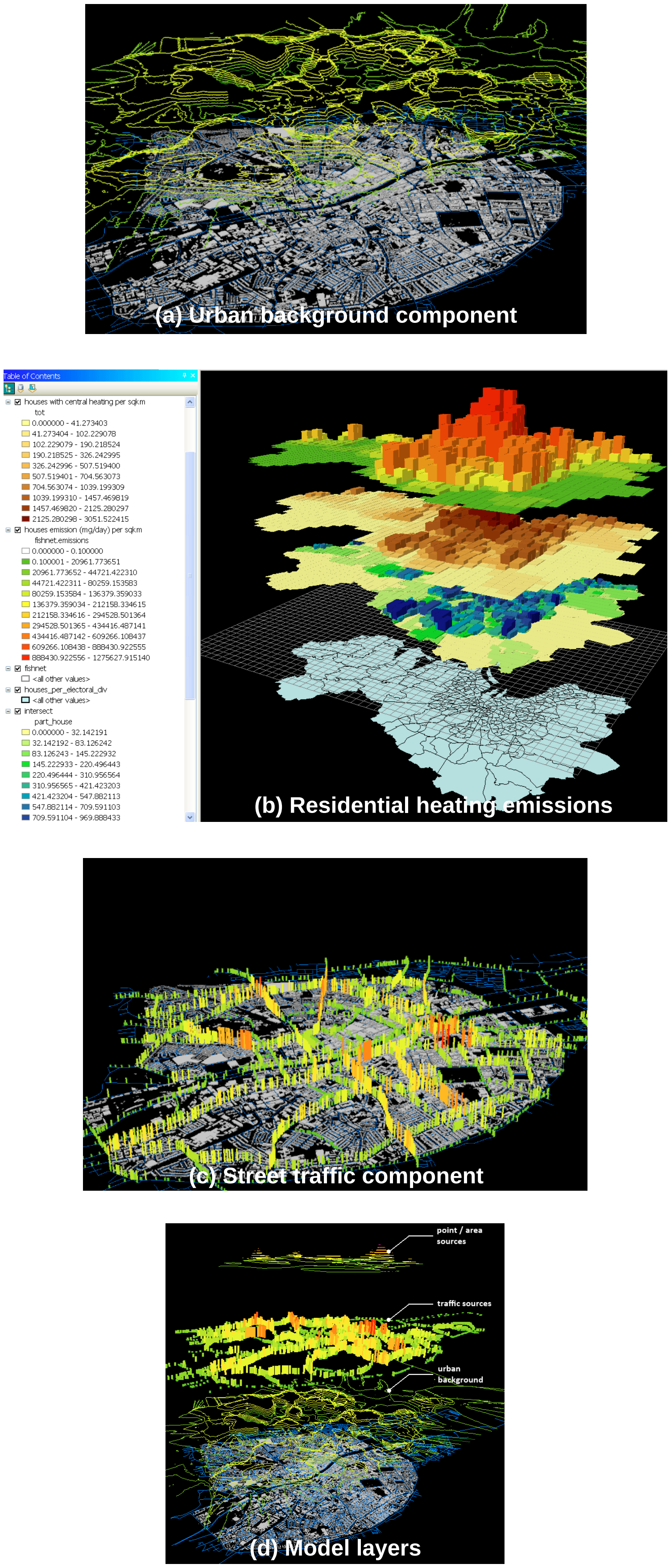

Figure 4.4. Visualisation of urban PM_{10} modelling in ArcGIS.

incorporated into the urban model. The dispersion of pollutants from sources belonging to these categories is modelled by using the Gaussian plume model with the Briggs Method (Briggs, 1973) for the lateral and vertical dispersion coefficients. The model is implemented in Python to be used as a tool in ArcGIS. In contrast to these large point sources, the availability of information on which to base an emissions inventory for the domestic sector is limited. Emissions from the domestic sector were derived for the Dublin urban area based on data on the "*Private dwellings in permanent housing units in each Province, County and City, with or without central heating*" for each Electoral District obtained from the National Population Census 2006 and 2011, combined with data on average natural gas usage for each household obtained from the Commission for Energy Regulation through Bord Gáis.

4.2.3 Contribution from traffic

The calculated background concentrations are a necessary input for the urban street model, along with weather conditions, traffic volumes and emission rates. One of the most important inputs is the street geometry: a relatively narrow street between buildings that line up continuously along both sides is called an urban street canyon and a stable circulatory vortex may be established within the street canyon if specific wind and geometry conditions are met. The combination of vehicle emissions and reduced dispersion in these circumstances can lead to high levels of pollution (Buckland and Middleton, 1999). The model selected for this task is the Operational Street Pollution Model (OSPM), developed by the National Environmental Research Institute, Denmark (Fig. 4.5), and validated in earlier modelling of air quality in Dublin city centre. The model was further validated for daily averages against measurements obtained at two separate locations, one in the city centre and one in the suburbs, for the month of March 2010. The results correlate well with the observed PM_{10} concentrations.

The OSPM is designed to calculate the dispersion of pollutants within urban street canyons, thus it is not appropriate for most roads in the GDA, where the city geometry is characterised by relatively wide roads flanked by trees and sparse low-rise buildings with gardens. The General Finite Line Source Model is chosen for modelling suburban traffic-related PM_{10} concentration levels. This model has also been validated in previous air quality modelling studies in Dublin (Ganguly et al., 2009), and for the PALM project is implemented using Python to work as a tool in ArcGIS (Fig. 4.4(d)).

4.3 Overall Pollutant Concentration at Street Level

The primary modelling scenario considered by the urban air quality modelling component of the PALM project was to create a GIS model for personal exposure to PM experienced by individuals in Dublin while commuting to work. The modelled concentration levels resulting from the modelling procedures

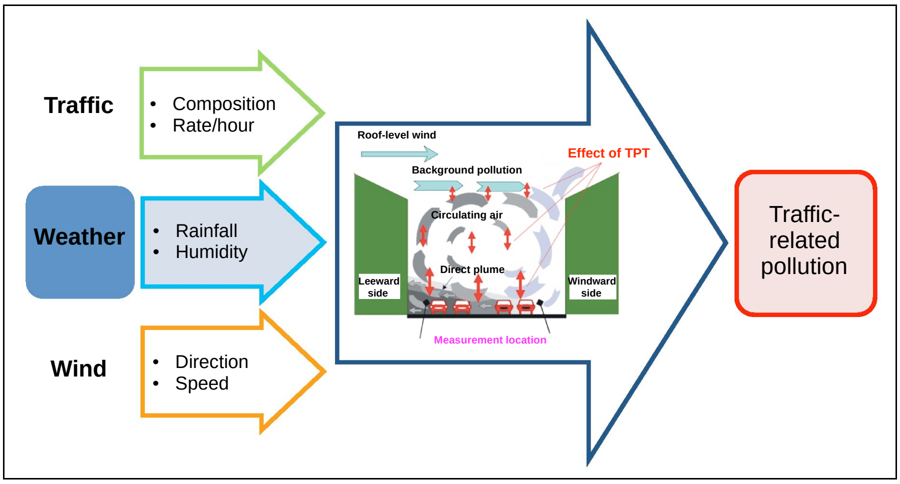

Figure 4.5. Traffic contribution in street canyons model, logic scheme. TPT, traffic-produced turbulence.

described above are imported into ArcGIS and combined to obtain total concentrations of PM_{10} throughout the GDA. A visualisation of such a calculation is presented in Fig. 4.4(d). The exposure of a set of individuals while commuting to work on different routes with various transport modes was modelled using this approach and tested against the measurements obtained in the personal exposure monitoring campaign described in Chapter 2. The correlation between the modelled and measured PM_{10} concentrations was determined for different test cases: the correlation was found to be high for the bus, bicycle and walking modes, but low for the train mode.

A solution for making the modelling tools and results available to the general public for self-assessment of personal exposure and for disseminating air quality modelling results was identified: ArcGIS online is suggested as an ideal tool for achieving this goal. Furthermore, the use of advanced technology emerging at the time of this study, such as cloud computing, is proposed and examined in the context of the employed GIS platform.

4.4 Urban Air Quality Modelling Results

The following section compares the results obtained from the PALM-GIS model with selected measurements of personal exposure to PM obtained within the measurement campaign described in Chapter 2 (Pilla and Broderick, 2015). A total of 2,424 PM_{10} measurements were used to test and validate the model, focusing on personal exposure during commuting trips at both peak and off-peak times using a range of transport modes (walk, bus, bicycle, and train). The measured and modelled data are compared in Fig. 4.6 and analysed in the model summary statistics and ANOVA presented in Tables 4.1 and 4.2, respectively. The identified coefficient of determination of 70.3% indicates that the PALM-GIS model is able to predict with good accuracy the exposure to PM_{10} of commuters during the trips used as test cases.

Figure 4.7 shows a plot of the modelled daily average PM_{10} levels for one of the scenarios (30 September 2010) used in the validation of the PALM-GIS model. The PM_{10} levels are modelled for all the road links with traffic volumes higher than 200 units per day (low traffic links are excluded for the presented simulation). The minimum modelled PM_{10} level is below 20 µg/m^3 (19.4 µg/m^3) while the maximum level is above 28 µg/m^3 (28.2 µg/m^3). The model is able to reproduce the spatial variation of the pollutant in an urban environment, where the overall pollution levels are affected by a wide range of sources. The modelled peaks in pollution levels are mostly due to high traffic volumes and city geometry (urban street canyons), while the contribution from regional sources accounts for almost 60% of the modelled levels (the predicted background levels for the scenario in Fig. 4.7 range between 16 and 19 µg/m^3). The influence of area and point sources on the total daily average modelled PM_{10} levels for the presented scenario is negligible.

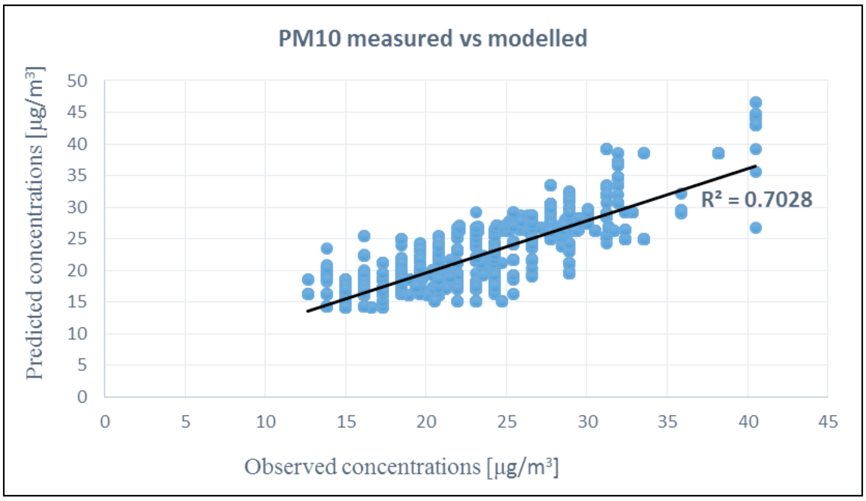

Figure 4.6. PALM-GIS: correlation between measured and modelled data (Pilla, 2013).

Table 4.1. Summary statistics for the PALM-GIS model.

R	R^2	Adjusted R^2	Standard error of the estimate
.838	0.703	0.703	2.994

Table 4.2. Analysis of variance (ANOVA) between measured and PALM-GIS modelled data.

Model	Sum of squares	df	Mean square	F	Significance
Regression	51,344.673	1	51,344.673	5,726.511	0.000
Residual	21,715.979	2,422	8.966		
Total	**73,060.652**	**2,423**			

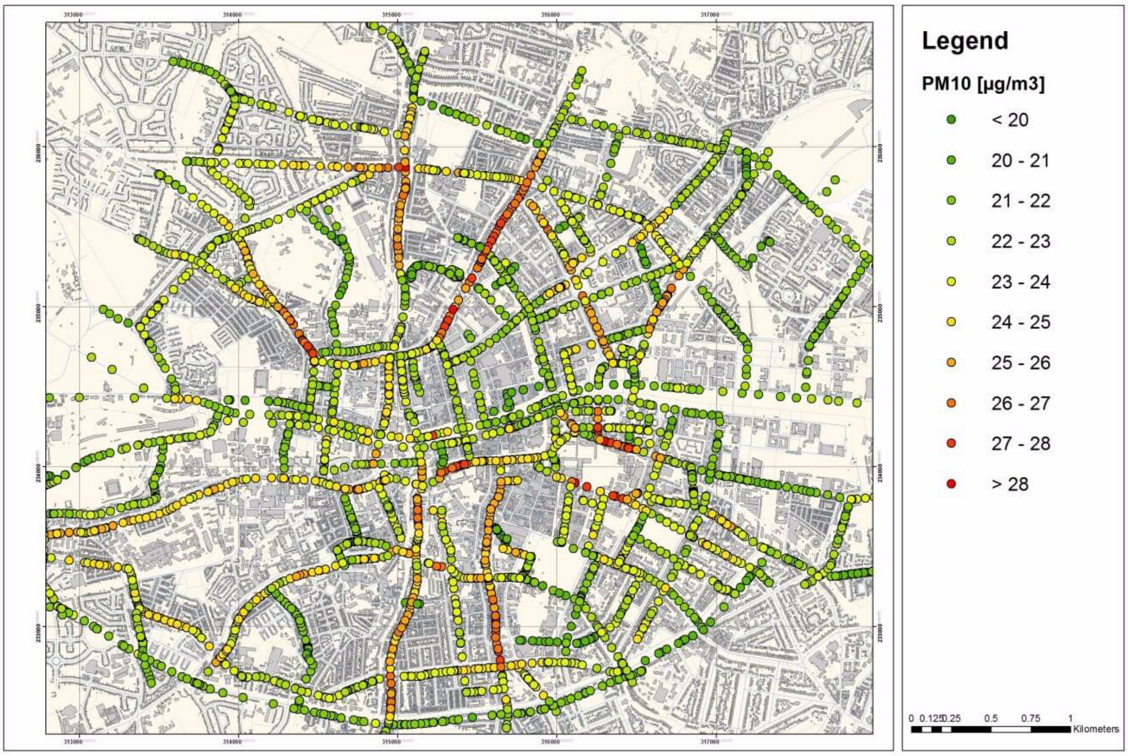

Figure 4.7. Spatial variability of the modelled PM_{10} levels.

Separate analyses of the data sets of commuter exposure used to test the PALM-GIS model were performed for each transport mode to obtain better insight into the model performance and limits in different situations. The five models considered were:

1. Static (72 measurements);
2. Walk (1,086 measurements);
3. Bus (943 measurements);
4. Bicycle (195 measurements); and
5. Train (128 measurements).

The set of 72 measurements obtained while subjects were standing without moving (for example at bus stops) was used as a baseline to test model performance in the absence of variability related to movement or transport mode micro-environment. The relevant summary statistics and ANOVA results for each model are presented in Tables 4.3 and 4.4, respectively.

Table 4.3. Summary statistics for the PALM-GIS model.

	R	R^2	Adjusted R^2	Standard error of the estimate
Static mode	0.939	0.881	0.880	1.407
Walk mode	0.838	0.702	0.702	3.038
Bus mode	0.823	0.677	0.677	3.091
Bicycle mode	0.880	0.775	0.773	1.407
Train mode	0.168	0.028	0.021	1.655

Table 4.4. Analysis of variance (ANOVA) between measured and modelled data.

	Model	Sum of squares	df	Mean square	F	Significance
Static	Regression	1,028	1	1,028	519	0.000
	Residual	139	70	1.98		
	Total	**1,166**	**71**			
Walk	Regression	23,591	1	23,591	2,555	0.000
	Residual	10,007	1,084	9.23		
	Total	**33,598**	**1,085**			
Bus	Regression	18,880	1	18,880	1,975	0.000
	Residual	8,992	941	9.56		
	Total	**27,872**	**942**			
Bicycle	Regression	1,312	1	1,312	663	0.000
	Residual	382	193	1.98		
	Total	**1,694**	**194**			
Train	Regression	10.0	1	10.0	3.66	0.058
	Residual	345	126	2.74		
	Total	**355**	**127**			

5 Conclusions

5.1 Summary of Research

The PALM project investigated methods for modelling an individual's personal exposure to air pollution, taking into account their activities and locations throughout a typical day. The project produced three different models:

1. A statistical model of the personal exposure of individuals in Dublin;
2. An improved version of the IAPPEM indoor air quality model; and
3. A set of dispersion models embedded in ArcGIS for ambient air quality in the GDA (PALM-GIS).

All of these models are available for further use.

The project included an intensive personal air quality monitoring field study focusing on the variation in exposure to PM experienced by residents of the GDA who work in office environments in the city centre. The results of this study were used to guide the development of the statistical capturing of this variation and deterministic models that allow these results to be extended to a wider range of individuals. These deterministic models have been integrated into a GIS platform for compatibility with city-wide and national environmental management activities. The indoor air quality modelling results were also validated using monitoring data obtained in targeted experimental measurement programmes.

5.2 Main Findings

5.2.1 Personal exposure monitoring data collection and analysis

The following findings arise from the results of the personal exposure monitoring campaign:

- The importance of indoor air quality on the overall impacts of air pollution on the health of a typical office worker has been highlighted. Exposure and uptake during indoor activities, such as working, cooking or at home, significantly outweighed those identified during outdoor activities, such as commuting.
- The extension of indoor air pollution control policy to the monitoring of air quality in the workplace and the enforcement of air quality standards indoors could bring about significant improvements in population health.
- The importance of considering both exposure and uptake of pollutants when comparing the health impacts of air pollution across differing activities has been highlighted. Using exposure alone as a measure of air pollution health impacts can result in significant misinterpretation of relative health impacts.
- The personal exposure measurement results indicate that there are often considerable differences between spatially representative ambient air quality measurements and the actual personal exposure concentrations experienced by individuals. This has implications for current ambient air policy, which relies heavily on representative ambient air quality measurements to ensure the protection of human health in urban areas.

5.2.2 Statistical/Stochastic exposure modelling

- The differences between mean personal exposure measurements and background air quality data identified in previous air pollution exposure assessments were confirmed in this study, which has implications for epidemiological modelling investigations.
- With a view to improving the strength of epidemiological modelling, a number of statistical/ stochastic methodologies for the prediction of personal exposure to PM_{10} were assessed. While the predictive performance of all techniques examined was reasonably good, the GRNN model and the Monte Carlo simulation approach produced the most reliable estimates of personal exposure.

- In addition to its strong ability to predict personal exposure among office workers, this study concludes that the Monte Carlo simulation technique also offers potential scope for improved transferability, with limited additional measurement data requirements. However, the extent of this transferability remains to be determined.

5.2.3 Indoor air quality modelling

- The state-of-the-art probabilistic model, IAPPEM, was developed to include a 1-min time resolution, a variable airflow rate, a modified PM_{10} deposition rate (which accounts for the variability in $PM_{2.5}/PM_{10}$ ratios), the incorporation of 12 simultaneously operating emission sources, and up to 15 interconnecting rooms.

- The ability of the IAPPEM to perform a detailed analysis of overall PM contribution from multiple different emission sources in a variety of different internal locations in a dwelling has been demonstrated. Additionally, the effect that both emission source location and internal household configuration have on PM transfer throughout a dwelling has been quantified.

- The IAPPEM was used to examine the potential accuracy of modelling inter-zonal airflow variations. An experimental validation concluded that a variable airflow can accurately predict $PM_{2.5}$ concentrations for inter-zonal airflow variations for durations of 10 min or greater, with increasing accuracy for longer durations. Additionally, a comparison between a time-weighted average airflow rate and a variable airflow rate reported that underprediction of $PM_{2.5}$ concentrations by up to 28% occurs using the time-weighted average airflow rate.

- The IAPPEM combines a time–activity model (which describes how individuals move through different zones in a dwelling) with the physical pollutant model, to create an overall air pollutant exposure model. The results of the simulations conducted in this study found that calculating exposure based on time-averaged profiles is a poor substitute for calculating exposure based on time–activity profiles.

5.2.4 Urban air quality modelling

- The project created a GIS-based air quality model for the GDA. This was achieved by integrating existing and self-implemented air quality models within a conventional GIS platform, and by generating input data for the models to allow the estimation of air quality at any location in the GDA. These steps were achieved by implementing various modelling tools:

  - A method to calculate urban background concentration levels;

  - A method to model the dispersion of pollutants from road traffic in urban street canyons;

  - A method to model the dispersion of pollutants from road traffic in general conditions; and

  - A method to calculate the dispersion of pollutants from point and area sources.

- As part of this work, the performances of various air quality models were assessed and the most suitable tools for modelling the dispersion of PM for different scales and locations selected. This was done in the context of the main objective – the assessment of the personal exposure of subjects moving between different locations in the urban area. This objective implies that a highly accurate solution at single locations is not valuable if it is combined with less accurate predictions for other locations.

- A new model for predicting PM_{10} background concentration levels in the GDA was created using machine learning algorithms. The background model uses ANNs to model the non-linear relation between historical PM_{10} data recorded at permanent air quality monitoring stations and the set of weather variables recorded at Met Éireann meteorological stations.

- The GIS model was validated by modelling the personal exposure to PM of commuters travelling to and from work in Dublin city centre using different routes and different transport modes and comparing the modelled data with measured data sets obtained with mobile sensors and GPS units. The synthesis of the modelling tools described above into this GIS platform can provide local authorities with a tool to calculate pollutant concentrations and to correlate these with other thematic layers, such as land use and population density, allowing localised peaks in air pollutants to be linked with particular activities.

5.3 Recommendations for Further Research

- The personal exposure monitoring campaign completed in this project identified the importance of indoor locations and specific indoor activities (such as cooking) for overall exposure. Considerable scope remains to continue this research through targeted monitoring programmes aimed at evaluating the contribution of exposure in the key indoor environments, such as homes, workplaces and schools.

- This project mainly focused on PM, and it can be readily extended to consider other pollutants. An assessment of the relative influence of outdoor and indoor concentrations on overall exposure to these pollutants and a comparison with the patterns identified for PM in this study would be valuable.

- The transferability of the statistical air pollution models developed in this project to other activity–location scenarios should be evaluated against an independent data set of measurements.

- The assignment of input parameter values obtained from the literature imposed a limitation on the IAPPEM indoor air quality model. A detailed experimental study, in which the primary aim is to determine air pollutant emission and deposition rates for the purposes of parameterising the computational model, is merited.

- The further development of the IAPPEM into a sub-zonal model would allow detailed examination of within-room variations in PM concentrations. Sub-zonal modelling would support the representation of the vertical and horizontal locations of emission sources, thus allowing investigation of the variation in an individual's exposure with distance from emission sources.

- The modelling methods developed in this project can be employed as an integrated research tool to assess links between individual health effects and personal exposure to air pollution. Similar previous epidemiological studies suffer from the combination of the need to compare temporally and/or spatially averaged air pollution data with individual-specific health information.

- The conceptual framework established in this project to model personal exposure to PM within a GIS platform can be extended to other environmental pollutants, such as other air pollutants and noise.

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Acronyms and Annotations

ANN	Artificial Neural Network
ESRI	Economic and Social Research Institute
FFNN	Feed Forward Neural Network
GDA	Greater Dublin Area
GPS	Global Positioning System
GRNN	Generalised Regression Neural Network
HRT	Human Respiratory Tract
IAPPEM	Indoor Air Pollutant Passive Exposure Model
ICRP	International Commission on Radiological Protection
NMB	Normalised mean bias
NO_2	Nitrogen dioxide
OSPM	Operational Street Pollution Model
PALM	Personal Activity and Location Model
PM	Particulate matter
PM_{10}	PM_{10}, particulate matter ≤10 µm
$PM_{2.5}$	$PM_{2.5}$, particulate matter ≤2.5 µm
RMSE	Root mean square error
TPT	Traffic-produced turbulence

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PALM: A Personal Activity–Location Model of Exposure to Air Pollution

epaResearch
Climate - Water - Sustainability
Identifying pressures • Informing policy • Developing solutions

Authors: Brian Broderick, Miriam Byrne, Aonghus McNabola, Laurence Gill, Francesco Pilla, James McGrath and Andrew McCreddin

The PALM project investigated methods for modelling an individual's personal exposure to air pollution taking into account their activities and locations throughout a typical day. This investigation and the developed exposure models employed high frequency personal air quality sampling.

Identifying Pressures

The adverse health effects of air pollution are well established, but previous studies on this topic have generally considered the average pollution concentration in an area rather than the specific concentration experienced by an individual. Variations in the locations (both indoors and outdoors) occupied by individuals and the activities in which they participate lead to variations in their exposure to pollution, in the uptake of air pollutants in their lungs, and in consequent health effects.

Informing Policy

A principal aim of the EU Clean Air for Europe programme (CAFE) is to develop long-term, strategic and integrated policy advice to protect against significant negative effects of air pollution on human health. The PALM project addresses this aim by evaluating the influence of different locations and activities on the air quality exposure of individuals in Dublin, Ireland. This information can be used to develop effective air quality management policies.

Developing Solutions

The PALM project investigated methods for modelling an individual's personal exposure to air pollution taking into account variations in their activity and location. The project produced three different models: a statistical model of the personal exposure of individuals in Dublin; an improved version of the IAPPEM indoor air quality model and a set of dispersion models embedded in ArcGIS for ambient AQ in the Dublin area (PALM-GIS). These models can be employed to develop strategies for the minimisation of individual exposure through lifestyle choices, and to provide subject-specific environmental data for air quality health studies.

Comhshaol, Pobal agus Rialtas Áitiúil
Environment, Community and Local Government

EPA Research: McCumiskey House, Richiew, Clonskeagh, Dublin 14.

Phone: 01 268 0100
Twitter: @EPAResearchNews
Email: research@epa.ie

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