

Use of an exposure model to explore the impact of residential proximity to a highway on exposures to air pollutants of an ambient origin

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Received: 20 August 2014 / Accepted: 14 April 2015 / Published online: 5 May 2015
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Abstract Air pollutant exposure models are generally applied to large populations living across wide urban areas, and most do not account for daily variation in activity patterns, which can result in exposure misclassification. Far fewer studies exist where exposure is modeled for specific individuals using detailed time-activity data. We employed a novel application of the US-EPA's Air Pollution Exposure Model (APEX) to simulate exposure levels for 51 residents living within a small study area (1.5 km²) bisected by a heavily trafficked highway in South Auckland, New Zealand. The model produced daily exposure estimates of nitrogen oxides (NO_x), carbon monoxide (CO), and particulate matter (PM₁₀) for the month of July, 2010. Inputs included pollutant and meteorological data monitored at sites positioned both upwind and downwind of the highway, as well as city monitoring sites north of the study area to represent work locations. A local resident survey provided time-activity diary input. The simulation was run once using the residents' home locations and four times with the population artificially placed 50 and 150 m downwind, as well as 50 and 150 m upwind, relative to the highway. For NO_x and CO, the population was 31–36 % more exposed when positioned 50 m downwind and 17–18 % less exposed at the upwind side ($p < 0.001$), compared to their actual home locations. An additional 100 m separation downwind resulted in a 56–71 % drop in total mean exposure

($p < 0.001$) and the difference in exposure levels for certain occupations varied by up to a factor of eight ($p < 0.05$). PM₁₀ exposure was comparatively stable across the area. The effect of residential proximity and position, occupation and work location, were assessed using generalized linear models (GLMs), followed by post hoc testing. This unique application of APEX shows good promise as a planning tool for assessing the potential benefits of a buffer zone between major roads and residential homes, for particular population groups.

Keywords Exposure model · Near highway · Traffic emissions · Carbon monoxide · Nitrogen oxides

Introduction

An individual's exposure to urban air pollutants is primarily dependent on the environments in which they spend their time, along with the quality of the ambient air in which these environments are positioned within. Hazardous microenvironments and "hot spot" zones throughout cities cause exposure between individuals to fluctuate substantially, even if they happen to be neighbors or live within the same household. This poses an interesting challenge for exposure science and epidemiology. A single fixed site monitor is an insufficient indicator of exposure for individuals living throughout a wide urban area. Ideally, air pollutant measurements, location, and activity data are recorded as the person moves through time and space, but this is impractical for studies assessing health data across large populations. Consequently, crude exposure estimates are generated and linked to health outcomes, often at the census area level.

Current preferred techniques include land use regression (LUR) and hybrid models, which incorporate multiple modeling aspects from a wide range of inputs. Although ideal for

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large numbers of individuals, hybrid approaches almost always rely on one or more datasets to be artificially generated, which increases uncertainty, possibly enhancing exposure misclassification, e.g., emissions dispersion, concentration interpolation, land use activity, or extrapolation of population inputs. The most reliable studies go one step further by validating and/or “training” (refining) the hybrid model with real-world time-activity and microenvironment exposure data (personal measurements), but these are generally limited to a small number of individuals.

A recent example came from Münster, Germany, where good agreement between modeled and measured PM₁₀ and PM_{2.5} exposure was achieved for a study of ten participants using a global positioning system (GPS), activity diaries, and ambient data, despite excluding monitored indoor microenvironment concentrations (Gerharz et al. 2013). Another study in Lieria, Portugal, estimated personal PM_{2.5} exposure using GPS data collected by five individuals, in combination with traffic emissions and dispersion models. Although they did not attempt to validate the modeled exposure levels, they compared well with those from similar studies in other European cities. The validation of model output is desirable but not always required, depending on the objectives of the study. Smaller studies which model exposure for just a few individuals have the advantage of greater accuracy yet there are limitations regarding statistical representativeness and applicability to a wider population. Accordingly, estimated exposures may not be useful in analyses of health census data, unless the results can be reliably extrapolated to wider areas.

Since the 1990s, the US Environmental Protection Agency (US-EPA) has released a range of large-area population exposure models. The most recent of these is the Air Pollution Exposure Model (APEX), which is designed to run exposure and/or inhalation (dose) simulations for large populations (groups of individuals) as they move across space and time, throughout a variety of microenvironments. Due to the ability to account for the movement of individuals, it is a significant improvement on traditional LUR methods and is consistently cited by the scientific literature as being one of the key human exposure models available (Fujita et al. 2014; Georgopoulos et al. 2009; Isaacs et al. 2008; Özkaynak et al. 2008, 2013; Xue et al. 2010; Zou et al. 2009).

APEX was recently applied and evaluated in a large-scale, multi-model study for the whole of Atlanta GA, USA (Dionisio et al. 2013). Modeled daily exposures to NO_x and CO were found to be in good agreement ($r > 0.82$) with those from hybrid models tested in the study, demonstrating the viability of using APEX as a standalone option. Dionisio et al. (2013) go on to state that exposure models will likely hold an advantage in fine-scale spatiotemporal applications and note the possible suitability for epidemiological investigations. However, a subsequent health effects-exposure investigation (cardiorespiratory emergency visits) did not produce

stronger estimates of effect than those from ambient monitoring data, with the exception of the association between NO_x/CO and asthma/wheeze (Sarnat et al. 2013). Despite these results, it is clear that spatiotemporally resolved personal exposure data have a future role in this area and associations will likely improve with model refinements and increased activity diary accuracy.

In this study, we use APEX to simulate the exposure of 51 near-highway residents to traffic-generated (NO_x, CO) and background source (PM₁₀) pollutants. Unlike previous population exposure studies covering wide areas, we focus on individuals living within close proximity to one another across a community no larger than 1.5 km². The community is largely comprised of low-income, ethnic minority groups, and household mould, overcrowding and a lack of adequate heating are common issues (Bullen et al. 2008; Butler et al. 2003; Cheer et al. 2002). Pre-existing health conditions are further compounded by exposure to emissions and dust resuspension from a large highway running through the community. Asthma, diabetes, and heart disease are of primary concern, and these afflictions are disproportionately high within the local population compared with the rest of the city (Cheer et al. 2002).

Time-activity profiles were derived from our own local surveys and then divided into eight different occupational groupings, based on the proportion of time spent in common microenvironments. We also use continuously monitored air quality data from Federal Equivalent Method (FEM) instrumentation at several sites across the study area, as opposed to concentrations approximated from emissions or air dispersion models. The effect of proximity and position of the home location relative to the highway is explored within the context of time spent away from the home, i.e., occupation, along with the proportion of time spent outside, are the main drivers of varying exposures. In addition, we shift the population around the study area for subsequent model runs in order to quantify the impact of proximity of the home. Much of the near-highway literature concludes that concentrations of primary traffic emissions (NO_x, CO, ultrafine particles) are typically elevated by approximately 50 % at the roadside compared to 100–150 m downwind (Karner et al. 2010; Pattinson et al. 2014; Patton et al. 2014). For long-term health reasons, some studies are now recommending a minimum separation of all residential buildings from highways, e.g., 100 m (Barros et al. 2013), but little is known about who would actually benefit most from a separation of such a distance.

Our aims are threefold. Firstly, we aim to simulate and compare exposures for worker and nonworker profiles assigned to a range of occupations. Secondly, we explore the effect of placing the study population directly within the roadside corridor (highest exposure zone) compared to further back from the road. We refer to this as the effect of proximity and position, relative to the highway and the direction of local

winds, respectively. Thirdly, we assess which occupational groups would obtain the least and most benefit (estimated reduction in exposure) if their home was to be shifted a minimum of 100 m in either direction, out of the highway corridor.

Our study is novel in that we take a population exposure model and apply it to a fine-scale study on the exposure impact of residential proximity to a major emissions source. We also believe that it is the first personal exposure modeling study conducted for New Zealand.

Methods

Study area and air quality monitoring

The study was primarily conducted in Otahuhu, South Auckland, a suburb bisected by a six-lane highway for which Annual Average Daily Traffic (AADT) exceeds 120,000 vehicles (NZTA 2013). The local monitoring campaign featured three air quality and meteorological stations at 5 m downwind, 134 m downwind, and 212 m upwind of the highway, relative to the predominant southwest wind direction (Fig. 1). This layout represents a typical near-highway monitoring configuration, with the three stations providing one immediate roadside site (5 m downwind), one downwind background site (within the potential spatial extent of highway emissions) and one upwind background site (likely outside the potential extent of highway emissions). Each monitoring station was equipped with instrumentation to continuously measure NO_x (chemiluminescence analyzer; model 200, Teledyne API), CO (gas filter correlation analyzer; model 300E, Teledyne API), PM₁₀ (BAM; Model FH62C14, Thermo Scientific) and wind data (anemometer; Models A101M & W200, Vector Instruments) at a time resolution of 10-min mean values. In the interest of capturing a wide range of pollutant concentration levels, which included coarse particulate from wood smoke, air quality sampling took place during a mid-winter month; specifically, midnight of July 1 to midnight of July 31, 2010. The dataset used in this study is a subset of a long-term highway corridor monitoring campaign, detailed in a separate article (Longley et al. 2014).

In addition to the primary study area, data from five other monitoring sites were used to represent residents' work locations (Fig. 2). This gave a total of six work locations (including Otahuhu itself) represented by a local ambient air monitor (Fig. 2). Data for the two monitoring sites north of Otahuhu, Penrose and Grafton (Fig. 2), were sourced from the Auckland Council which operates identical models of instrumentation to those deployed by our study (Auckland Council 2005). As the local council does not have other monitoring sites in the vicinity of South Auckland, the other three destinations of East Tamaki, Papatoetoe, and Mangere used replicate data from the

upwind background site shown in Fig. 1. Note that all three sites are similarly positioned approximately 215 m upwind from a major road (Fig. 2). Essentially, we can either make the assumption that our upwind background site represents levels that would be found at a similar site within the neighboring suburbs or that the local worker does not leave their home suburb. The purpose was to be able to replicate actual time-activity-location patterns as closely as possible, within the exposure model.

Participant survey methods

To gain a realistic understanding of how local residents actually spent their time, time-activity data was required for the model. Due to a lack of existing time-activity data for Auckland at the temporal resolution and level of detail required, we opted to conduct our own survey of local residents by means of door-to-door recruitment. Prior to conducting the surveys, the survey was reviewed and approved by the University of Canterbury Human Ethics Committee (HEC 2011/94). The aim was to recruit 25 participants from within the immediate roadside corridor (<150 m down/upwind) and 25 outside of the corridor, yet still within potential influence of the highway (>150 and <500 m down/upwind). Some residents asked the interviewer to return at a different time. In keeping these appointments, the number of participants exceeded the target by one. Each participant was asked to provide a timeline of their movements for a typical week. Targeted door-to-door recruitment for the purposes of time-activity surveying has been used in previous exposure modeling research (Brugge et al. 2013; Kaufman et al. 2012). With the exception of short trips within the local area (15 min), each activity lasted a minimum of 30 min. For most participants in full-time employment, their Monday to Friday schedule was generally identical but punctuated by regular sports practice, club meetings, shopping, and social outings on particular evenings. The majority of part-time workers and the unemployed or retired also had routine schedules that generally revolved around child care (school times) and/or regular recreational activities. Common weekend activities included attending church, visiting friends/family, and local recreation such as sports and fishing. None of the participants routinely left the wider study area, and we were not interested in factoring in atypical movements such as long-distance travel.

As this study only focused on exposure and not inhaled dose, it was not necessary to gather sensitive demographic data such as age, height, and weight. However, participants were asked to provide their work location, type of employment and type of work environment (building and ventilation type), as well as the approximate location (the suburb) of any regular activities outside of work. These data were used in combination with the time-activity diaries to assign the range

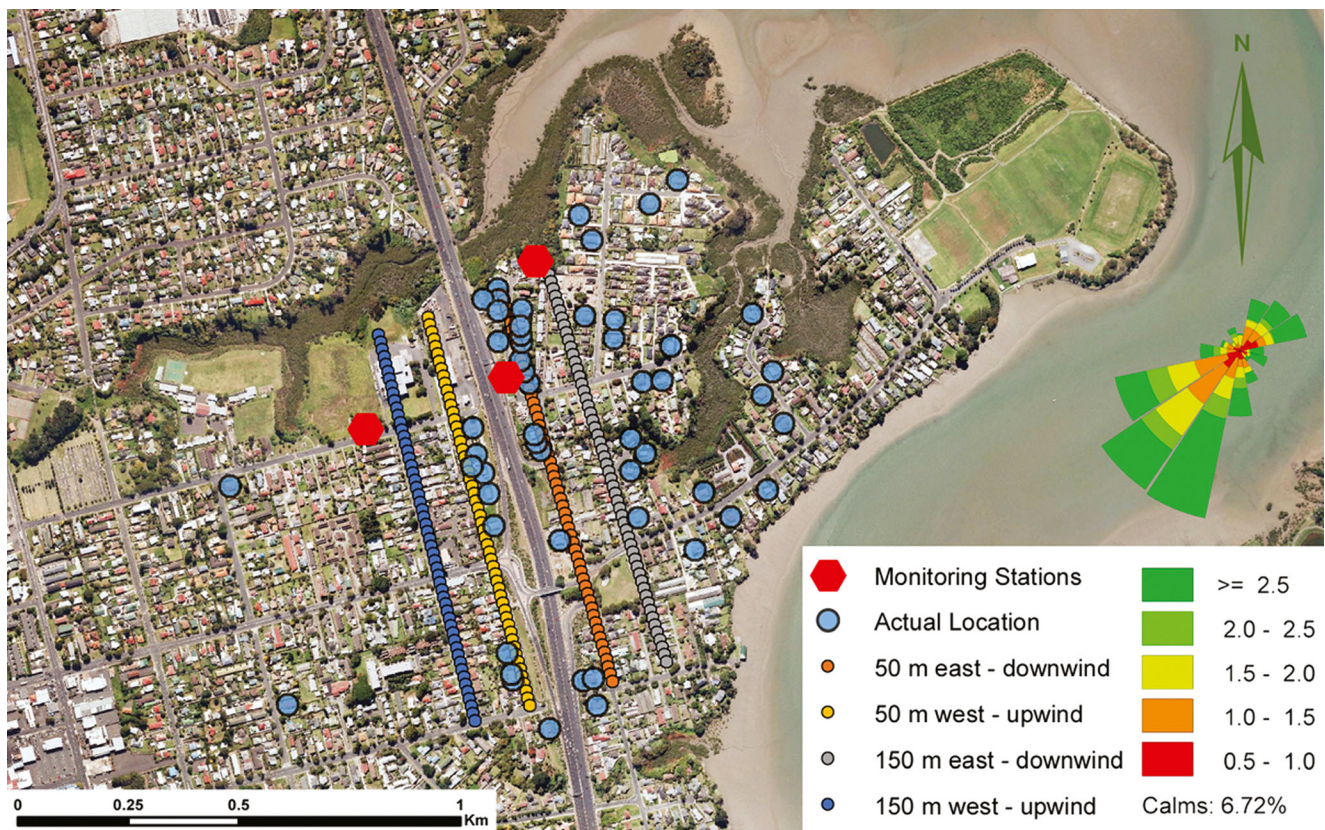


Fig. 1 Study area showing wind direction and speed (m/s), location of monitoring stations, actual locations of study participants' homes, and simulated participant home locations, relative to the highway. Note that

actual resident locations are inexact to preserve anonymity (randomly shifted 1–2 properties either side of home address)

of microenvironments and air monitoring locations that participants passed through during a typical week.

Exposure model inputs and configuration

APEX allows for a highly complex variety of model inputs which can be used to estimate exposure and pollutant dose for individuals living and working in numerous types of microenvironments. Outcomes are dependent on a wide range of user-input environmental (ventilation systems, presence of gas utilities, air conditioning, window use, etc.) and physiological parameters (age, gender, weight, height, etc.). We omitted much of this information as it was not required for this application, e.g., physiological parameters are used in the calculation of dose, but not for exposure.

At the most basic level, APEX assigns an average exposure to each environment/microenvironment based on time spent in the environment and estimated concentrations within the environment, which are derived from an calculated concentration of indoor and outdoor sources, based on penetration factors and air exchange rates (AERs). Local air quality and meteorological data from multiple stations is needed as the primary model input, along with time-activity information.

The following equations show how APEX calculates concentrations in different microenvironments:

$$E_{\text{tot}} = \sum_i f_i * C_i$$

where

E_{tot} total exposure, expressed as an average concentration for the exposure period

f_i time fraction spent in the microenvironment

C_i concentration in the microenvironment

Exposure for individual microenvironments are calculated as follows:

$$C_i = C_{\text{out}} * p_i + S_n$$

where

C_i concentration within the microenvironment

C_{out} outdoor concentration at microenvironment location

p pollutant penetration factor

S attribution of sources in the indoor microenvironment

APEX was run without the inclusion of pollutant concentrations originating from indoor sources, or S . As residents

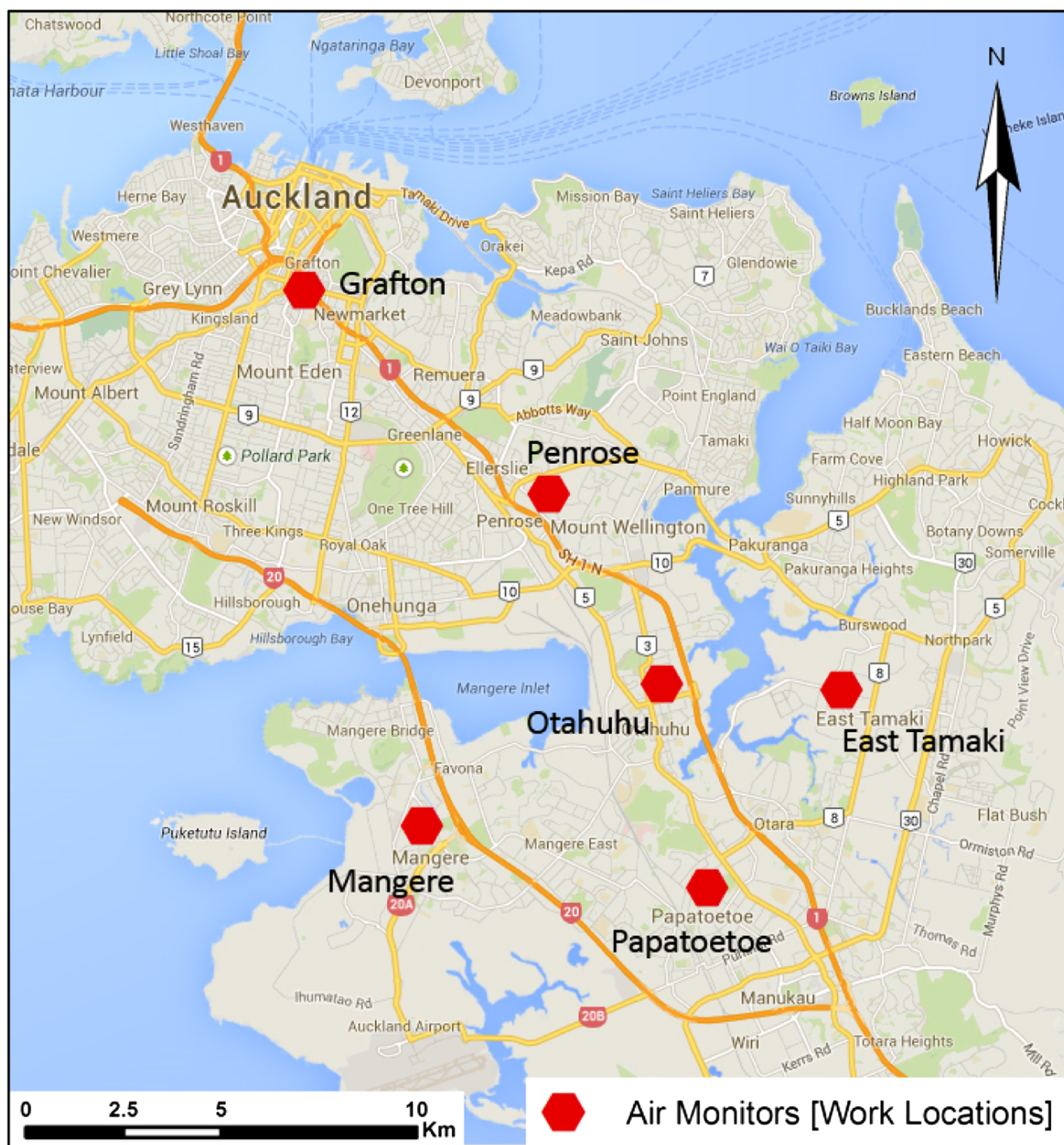


Fig. 2 Map showing wider study area and positions of other monitoring stations. The primary study area of Otahuhu is near the center of the map

have control over sources originating from inside their homes but little to no influence on ambient air quality, including indoor sources was not an objective of this study.

In addition to our own local pollutant and meteorological data, we added air exchange rates (AERs) measured inside a 1960s weatherboard home with the windows and doors closed, situated next to the downwind background station (Fig. 1). AERs were measured by continuously logging the

decay of carbon dioxide (CO_2) concentrations (model GMP343, Vaisala) after releasing a set of 12 g CO_2 cartridges. This technique has been developed and validated both in the lab and within field studies (You et al. 2012). Five AER measurements were made over a 2-week period during the pollutant monitoring campaign. The range of AERs ($1.4\text{--}2.8\text{ ac h}^{-1}$) was then applied to the residential microenvironments for all individuals, across all days within our study. Although it

would have been ideal to measure within both older and newer homes, the type of dwelling used is most representative of the housing stock within Otahuhu and throughout other low-income areas of South Auckland. AERs for larger building types, as well as penetration factors for vehicle types, were left to the default parameters based on data from US cities (see Appendix 1 for full table of parameters).

Exposure model application

APEX is designed to run large simulations for thousands of profiles (individuals) across wide urban areas. It is a stochastic model, where individual profiles (demographic and time-activity data) are randomly assigned to area units (sectors) within the defined study zone. Similarly, a value for each parameter relating to each microenvironment is randomly assigned, based on a range of pre-determined values. For example, no two buildings will have exactly the same penetration factors and air exchange rates, but similarly-sized buildings will likely fall into a range of known parameters (previously measured) for that type of building and ventilation system. Most applications of APEX use pre-existing human activity databases in combination with known microenvironment parameters. When APEX is run in this way, an unlimited number of profiles can be generated, with the results reflecting random scenarios (different activity patterns in varying microenvironments), for the same individual, over the study period.

We removed the stochastic profile element by assigning each individual diary day, to each participant's exact geographic location at home and work (sectors). The same initial random number seed was used for all model runs, eliminating possible confounding by stochastic elements when comparing different runs. The only random element remaining was the assignment of parameters to each microenvironment. As the order of simulated profile output is also randomized, this was controlled for by generating 255 profiles (4 for each person) and using the results for the first instance of each profile, across all model runs. Figure 3 illustrates the way in which APEX calculates concentrations in order of sequence.

Appendix 2 provides an example of the detail of diary input into APEX for a worker who wakes at 0530, spends 30 min getting ready and having breakfast and takes a 15-min commute before commencing work at 0615. Each time a microenvironment changes, a different activity and location code apply. These included both indoor and outdoor environments in private, residential settings, at workplaces, and in publicly accessible areas such as parks and shopping malls. A complete list of the microenvironments used (17 of 28 available) and the concentration estimation method employed for each is provided in Appendix 3. For 51 persons over 30 days, assigning activity and location codes required transforming written diary data into 10,502 lines of code, resulting in an exposure simulation of 1530 individual person days. Summary statistics for

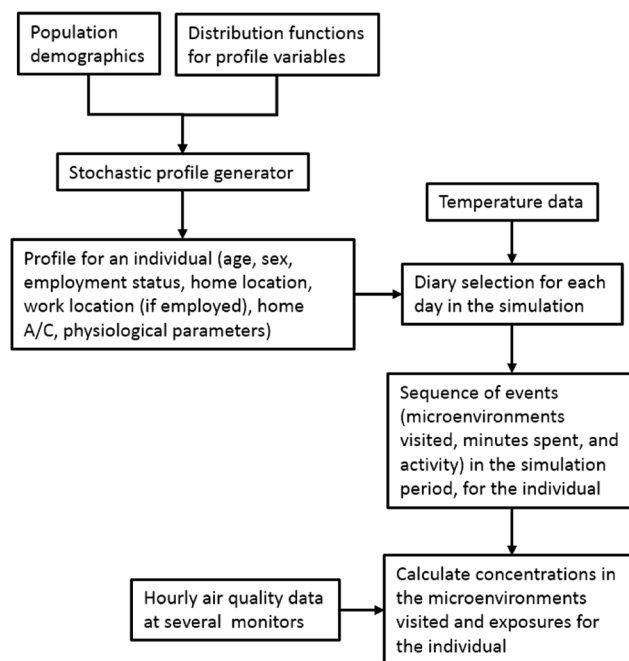


Fig. 3 Flow diagram showing sequence of APEX model process

percentage of time spent in different activities and environments are provided in Appendices 4 and 5, respectively. The simulation was run once using the residents' home locations, and four times with the population artificially placed 50 and 150 m downwind, as well as 50 and 150 m upwind, relative to the highway (refer to Fig. 1). Although APEX includes a module to simulate commuting, we did not include exposures while commuting in our study as the focus was on ambient exposures and the impact of near-highway living.

Analysis of model output

The resultant mean exposure value for each individual (30-day simulation) was pooled into one of eight occupational groupings, based on time spent in common microenvironments, such as ventilated offices and outdoor work environments. All occupational groupings are self-explanatory with the exception of the unemployed or retired group. These profiles were divided into two groups, one being active and the other inactive. An unemployed or retired participant who spent more than 70 % of their time inside their home (not going outside or leaving the property) was defined as inactive (see Appendix 5). This gave a range of 60–360 simulated exposure days for each group (2–12 individuals).

Additional analyses on the daily exposure data were performed by applying a generalized linear model (GLM) to the eight groupings. The primary model tested proximity and position of home location, along with occupational group, as the main effects (independent variables). Post hoc Bonferroni tests were used to assess significance between means for all possible pairings by occupation and position relative to the

highway, i.e., pairs both within and between exposure groupings. A second GLM tested the effect of work location on exposure. A single GLM could not be used alone due to a lack of variance across categorical variables, e.g., all unemployed/retired profiles have the same work location of “Home.” For clarification, all variables used in the GLM analyses are provided in Appendix 6. To check for any bias within the models, relationships between all variables were tested within a correlation matrix. All analyses were tested for significance at alpha level 0.05 but are reported as <0.05, <0.01, or <0.001, as per the results. The analyses were run within a statistical software package (Statistica 10, StatSoft Inc.).

Results

Fixed station measurements

Table 1 provides the summary statistics for all local and work destination monitoring sites for the duration of the modeling campaign (refer to Fig. 2 for geographical locations). Within the local study area, the monitor 5 m downwind (representing the roadside corridor) recorded concentrations ~50 % (NO_x) and ~43 % (CO) greater than each of the sites further back from the road, which were almost equal. Despite having considerably less traffic capacity (four lanes instead of six),

measurements at the street canyon site were 25 % (NO_x) and 30 % (CO) higher than at the highway roadside in Otahuhu.

Figure 4 illustrates the strength of the street canyon effect, with the Grafton site showing a clear bi-modal peak representing the rush hour traffic flows. The late rush hour peak at the highway area is suppressed by strong afternoon winds. Although there is a significant emissions source at Otahuhu, it is heavily modulated by local meteorology. This is important in the context of utilizing residents’ time-activity-location dairies, because there are major diurnal fluctuations in the spatial extent of traffic markers (wider during mornings and evenings). For a full discussion on spatial extent in this area, see Pattinson et al. (2014). Variation in PM₁₀ between sites was minimal.

APEX model output: exposure estimates

Proximity to highway

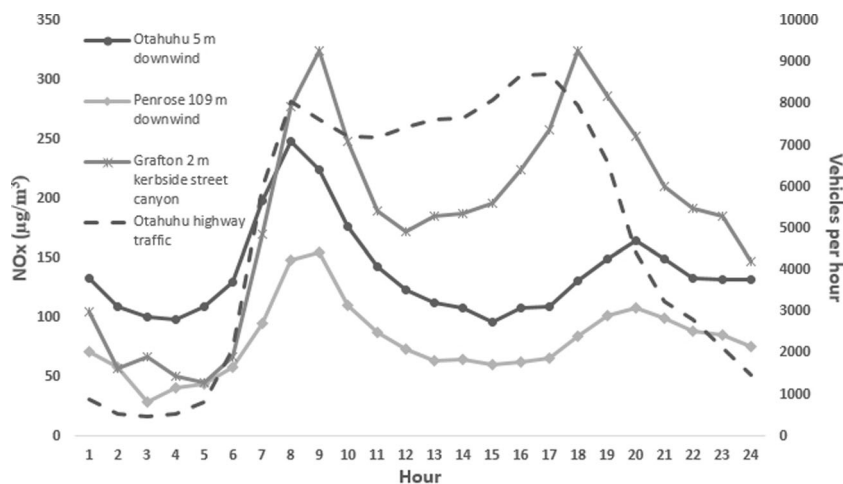
For resident proximity to highway (both sides of highway), there was an inverse relationship for NO_x ($r=-0.28$) and CO ($r=-0.32$), but no trend for PM₁₀ ($r=0.00$). When residents’ actual home locations were shifted to the immediate roadside corridor at the downwind edge (50 m), exposure for the group increased by 31 % for NO_x ($F_{39}=10.3$, $p<0.001$) and 36 % for CO ($F_{39}=10.7$, $p<0.001$). However, when downwind

Table 1 Fixed station mean results from hourly measurements for July 2010

Fixed station position and pollutant	Mean (30 days)	SD	Min hourly	Max hourly	Median	95 % CI
NO_x (µg/m³)						
5 m east of highway—downwind, Otahuhu	138.0	113.2	0.0	776.7	124.9	10.1
134 m east of highway—downwind, Otahuhu	68.2	73.6	0.0	562.7	42.6	5.0
212 m west of highway—upwind, Otahuhu	66.2	71.2	4.1	499.6	37.9	4.8
109 m east of highway—downwind, Penrose	80.2	61.6	0.2	381.2	71.9	5.9
2 m south of busy road in urban street canyon, 250 m east of highway, Grafton (CBD)	184.1	126.4	0.0	662.7	168.6	13.4
CO (ppm)						
5 m east of highway—downwind, Otahuhu	0.94	0.83	0.04	5.84	0.79	0.07
134 m east of highway—downwind, Otahuhu	0.53	0.49	0.08	2.36	0.33	0.05
212 m west of highway—upwind, Otahuhu	0.55	0.62	0.08	3.32	0.28	0.04
109 m east of highway—downwind, Penrose	0.40	0.40	0.01	2.64	0.30	0.03
2 m south of busy road in urban street canyon, 250 m east of highway, Grafton (CBD)	1.34	0.95	0.00	4.67	1.26	0.10
PM₁₀ (µg/m³)						
5 m east of highway—downwind, Otahuhu	19.2	13.2	0.1	76.1	16.7	1.4
134 m east of highway—downwind, Otahuhu	21.2	14.5	0.8	96.4	17.4	1.6
212 m west of highway—downwind, Otahuhu	16.5	11.7	1.2	70.3	13.4	1.2
109 m east of highway—downwind, Penrose	17.2	11.3	0.0	71.6	15.1	1.3
2 m south of busy road in urban street canyon, 250 m east of highway, Grafton (CBD)	20.6	12.6	0.7	84.3	18.5	1.5

Refer to Fig. 2 for map of monitoring locations

Fig. 4 Diurnal NO_x concentrations closest to the roadway, July 2010



separation was extended to 150 m, exposure decreased by 56 and 71 % from the 50-m point, respectively (Table 2). Mean differences at the upwind side were only statistically significant at the 150-m point. Exposures ranged from 31 to 48 % less than 50 m within the downwind corridor or from the residents' actual locations (Table 2). Note that 13 of the 51 simulated profiles reside within 50 m downwind of the highway (see Fig. 1).

Proximity to highway and occupational group

The main effects on exposure were highly significant ($p < 0.001$) for all three pollutants (Tables 3 and 4). Proximity and position were important, as was occupational group, irrespective of where participants lived. A basic sensitivity analysis, where the three groups of the smallest sample sizes were removed, showed that the main effects remained highly statistically significant at $p < 0.001$. Additionally, there was no correlation between home position and occupational group ($r = -0.06$).

Figures 5, 6, and 7 illustrate the varying levels of exposure grouped by occupation and proximity/position relative to the highway. Figure 8 provides an illustration of day-to-day NO_x variation throughout the study period, for each occupational group. For all three pollutants, outdoor laborers were the most exposed group and the unemployed or retired, inactive group, the least exposed. While variation within the results for PM_{10} was minimal, post hoc testing revealed multiple statistically significant differences within and between groups for NO_x and CO (Appendices 7 and 8). Those who spent more time doing outdoor activities at home, or more time near traffic at work, faced increased exposure at the 50-m downwind position. NO_x exposure grew 47 % ($F_{229} = 10.3$, $p = 0.005$) and 93 % ($F_{229} = 10.3$, $p = 0.021$) for the unemployed/retired-active and security guard groups, respectively (Fig. 5 and Appendix 7). For the same occupations, CO exposure increased 53 % ($F_{229} = 10.3$, $p < 0.001$) and 157 % ($F_{229} = 10.3$,

$p = 0.004$). All occupations benefited from a further 100 m separation from the highway, with 53–75 % reductions for both pollutants ($p < 0.05$). Again, the most substantial reductions were seen for the unemployed/retired-active and security guard groups. Across all groups, the range between the least exposed (unemployed/retired-inactive) and most exposed group (outdoor laborer) varied by a factor of 6 and 8 (NO_x , CO) from 50 m downwind to 100 m downwind. This shows that persons living just 100 m from one another can potentially have an eightfold variation in ambient exposure. Complete summary statistics for the occupational groups by proximity and position can be viewed in Appendices 7, 8, and 9.

Proximity to highway and work location

An additional GLM was run to test the effect of work location (Tables 5 and 6). Mean exposure values by work location are illustrated in Fig. 9. Although there was a moderate strength statistically significant correlation between work location and occupation ($r = 0.41$, $p = 0.03$), this was only due to the unemployed/retired group all having the same work location of "Home." With this occupational group removed, the correlation ceased to exist ($r = 0.006$) yet the main effect of "Work Location" remained significant at $p < 0.001$ within the GLM. Thus, we can be confident that work location has a significant influence on the simulated profiles, independent of occupation.

Discussion

Monitored ambient levels versus modeled exposure

The mean values recorded at the nearest associated monitoring station were a factor of 2.3–2.8 (NO_x , PM_{10}) times greater than the overall mean for the grouped (by proximity) exposure profiles. For CO, this divergence was even greater at 2.5–4.8

Table 2 Total group differences in ambient month-long exposure for July 2010 (1500 individual profile days simulated)

Proximity of home and pollutant	Mean (30 days)	SD	Min daily	Max daily	Median	95 % CI	% Change in mean exposure from
NO_x (µg/m³)							
Actual location	45.2	36.6	0.6	228.9	34.9	1.8	Actual location
50 m east—downwind	60.0	41.1	0.4	232.6	53.8	2	31
50 m west—upwind	48.8	37.8	0.6	228.9	39.7	1.8	8
150 m east—downwind	26.3	21.9	0.5	124.1	20.6	1.1	-42
150 m west—upwind	25.2	20.7	1.8	158.3	18.7	1.0	-44
CO (ppm)							
Actual location	0.27	0.22	0.00	1.32	0.22	0.01	Actual location
50 m east—downwind	0.37	0.25	0.00	1.35	0.34	0.01	36
50 m west—upwind	0.31	0.23	0.01	1.32	0.26	0.01	15
150 m east—downwind	0.11	0.11	0.00	0.78	0.07	0.01	-60
150 m west—upwind	0.18	0.14	0.01	1.23	0.14	0.01	-31
PM₁₀ (µg/m³)							
Actual location	7.0	3.9	0.4	27.1	6.3	0.2	Actual location
50 m east—downwind	7.0	4.0	0.3	27.1	6.2	0.2	0
50 m west—upwind	6.7	3.8	0.3	27.1	6.0	0.2	-4
150 m east—downwind	7.6	4.1	0.3	27.1	6.9	0.2	9
150 m west—upwind	5.8	3.3	0.4	26.8	5.3	0.2	-17

Significant differences between groups are indicated in italics ($p < 0.01$, $\alpha = 0.05$)

(Tables 1 and 2). These basic results alone clearly highlight the protective effect of the residential building envelope, and the importance of time spent in other environments, away from home. Even with relatively high air exchange rates, naturally ventilated environments can help to downscale indoor levels to half those of outdoor, when no indoor emissions sources are present (Jones et al. 2000; Ní Riain et al. 2003). Although indoor sources are important for personal exposure assessment, indoor residential sources of NO_x and CO are typically limited to unflued gas appliances, fireplaces, and tobacco smoke. Conversely, ultrafine particles (UFPs) are emitted in very high numbers during numerous household activities, especially cooking (Buonanno et al. 2014). Wood burners, other indoor combustion activities and resuspension from household movement can contribute to PM₁₀ levels, but in this case, we are only interested in the impact of being in close proximity to a highway. The rationale for this is that the generation of indoor sources at home is something that can be controlled by individuals whereas outdoor air quality cannot. The pollutants chosen for our study are appropriately suited for representing fresh exhaust emissions (NO_x, CO), traffic-generated coarse particulate, and the urban background plume (PM₁₀).

Overall effect of proximity

The overall effect of proximity to the highway on mean NO_x and CO exposure was substantial. If the study population were housed within 50 m downwind of the highway, exposure would be 32–37 % greater than when dispersed throughout the community (actual locations, Fig 1). If the separation was increased a further 100 m outside of the immediate downwind corridor, exposure would decrease 56–70 % (Table 2). Exposure at the upwind side of the corridor was also considerably less (16–18 %). The roadside to downwind background (134 m) decrease from the monitored data was lower at 51 and 44 %, for NO_x and CO, respectively (Table 1). One factor explaining this difference may be time spent outside (by active individuals) elevating the roadside group mean, increasing the gap in simulated exposures.

The majority of roadside studies report an approximate 50 % drop in NO_x and CO within 150 m, but no decay trend

Table 3 GLM multivariate tests: proximity to highway and occupational group

	Test	Value	F	Effect-df	Error-df	p value
Intercept	Wilks	0.09	794	3	228	<0.001
Proximity/position	Wilks	0.27	32	12	604	<0.001
Occupational group	Wilks	0.32	15	21	655	<0.001
Proximity/position × occupational group	Wilks	0.70	1	84	683	0.44

Table 4 Whole model *R*: proximity to highway and occupational group

	Multiple- <i>R</i>	SS-model	<i>df</i> -Model	MS-model	SS-residual	<i>df</i> -Residual	MS-residual	<i>F</i>	<i>p</i> value
NO _x	0.798	97514.4	39	2500.4	55705.9	229	242.2	10.3	<.001
CO	0.803	3.9	39	0.1	2.1	229	0.0	10.7	<.001
PM ₁₀	0.690	1034.7	39	26.5	1136.9	229	4.9	5.4	<.001

for PM₁₀ (Karner et al. 2010). Our findings are in agreement and also show that when time-activity-location patterns are taken into account, ambient exposure reductions can potentially increase. This has important implications not only for planning and development, but also for social housing policy in regard to the placement of sensitive individuals and groups. The long-term impact of living within the highway corridor can be considerable for children, the elderly, and those suffering from significant illness and/or respiratory afflictions (Favarato et al. 2014; Perez et al. 2013). This is a concern within the local study context as its population suffers from disproportionately high rates of respiratory disease and diabetes (Cheer et al. 2002). Immediately south of Otahuhu, there is a primary school within 10 m of the highway which also features an early childhood center on school grounds. For some residents living in South Auckland roadside communities, time spent away from the highway corridor could be quite limited.

Effect of occupation by proximity

To the best of our knowledge, no previous exposure modeling simulation has explored the influence of occupation, whereas personal monitoring by different occupations is more commonly investigated. Most of these tend to focus on high-exposure occupations such as those who work within heavily trafficked zones (policemen, taxi drivers, toll gate employees) and potentially toxic workplace settings (commercial cleaning operations, beauty salons, autobody repair workshops) where volatile organic compound (VOC) vapors and aerosols can be present in high concentrations (Bello et al. 2009; Kisku et al. 2013; Tsigonia et al. 2010). Very few personal monitoring studies exist for NO_x and those for CO usually include significant indoor sources (di Marco et al. 2005; Raw et al. 2004). For better comparability, we refer to research utilizing markers of fresh traffic emissions which do not have strong within-residence sources.

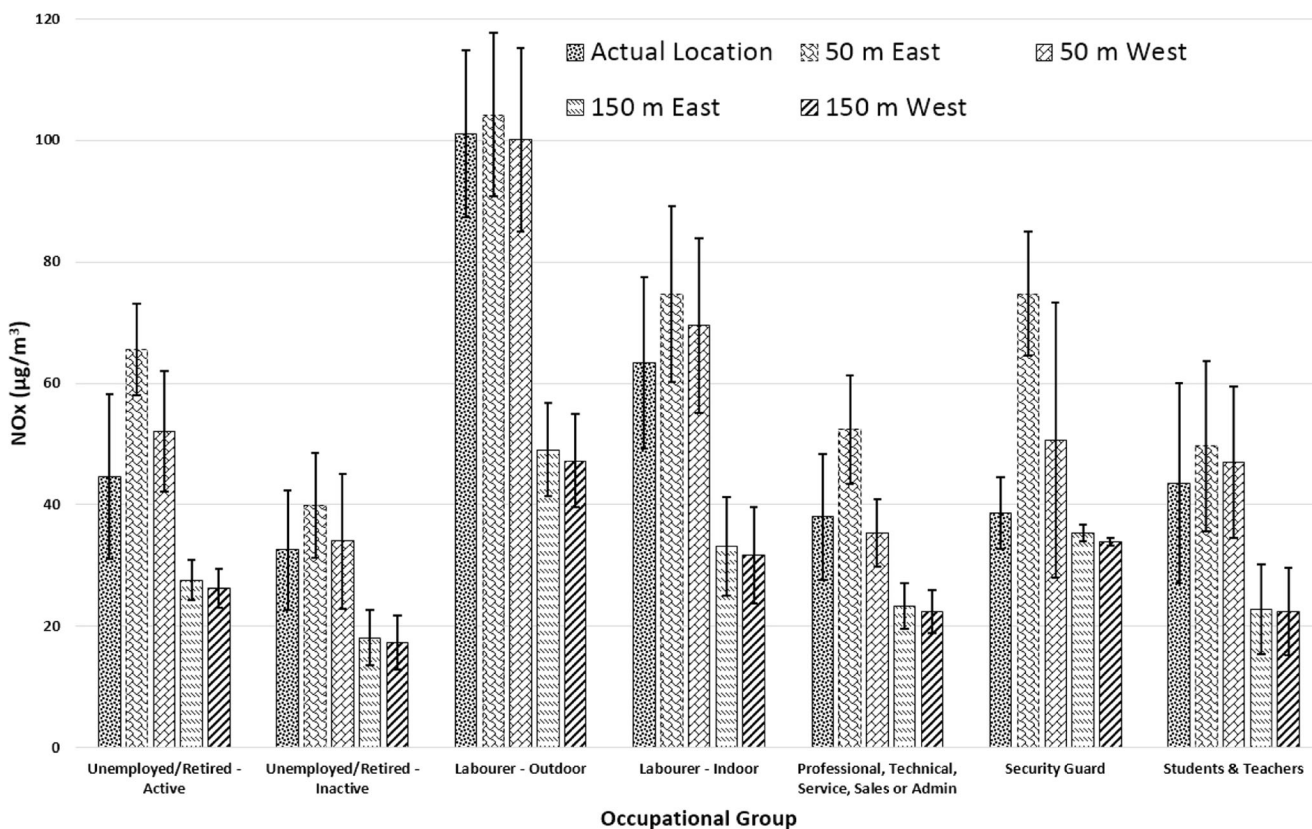


Fig. 5 Simulated total mean ambient NO_x exposure by occupational group for the month of July, 2010. Error bars denote 95 % confidence limits

An occupational study of benzene (a highly carcinogenic VOC present in petrol fumes) exposure for 50 workers in Athens, Greece, found the strongest predictors were proximity of home location to heavy traffic, time spent outdoors, and time spent in transportation (Chatzis et al. 2005). Time spent outdoors explained the link between occupation and high personal exposure levels. These findings are reflected by our results, with the outdoor laborers and security guards consistently the most exposed, while professionals, office workers, teachers, and students were the least exposed (Figs. 6, 7, and 8). Similarly, exposure for those who spent more time outdoors at the home location (unemployed/retired, active) was 43–45 % (NO_x , CO) and 46–50 % (PM_{10}) greater than for those who spent most of their time indoors. For these groups, differences for NO_x and CO were only significant ($p < 0.05$) within the roadside corridor (both sides) but shifting location did not render PM_{10} nonsignificant anywhere. Similar levels of significance, again for the roadside corridor only (NO_x , CO), were found for other paired groups such as outdoor laborer versus indoor laborer. Those working in large warehouses and factories were 28–37 % (NO_x , CO) and 38–40 % (PM_{10}) less exposed than carpenters working outside. Further back from the highway, the only occupation for which exposure was statistically significantly ($p < 0.05$) higher for NO_x and CO was outdoor laborers, and only when compared to those who spent most of their time indoors at home

(unemployed/retired-inactive). With the exception of PM_{10} , these findings show that when living outside of the highway corridor, the effect of occupation is nonsignificant for most but remains somewhat important for those who may be working outside near busy roads.

These results also show that proximity of residence has a far stronger influence on personal exposure to ambient pollutants than occupation. A VOC study of 100 residents in London, UK, found that 50–75 % of variability within personal exposure for most compounds was explained by the home environment (Delgado-Saborit et al. 2011). Extensive source apportionment work in Helsinki, Finland, concluded that traffic emissions were second only to domestic cleaners, as the strongest origin of indoor VOC concentrations in non-smoking households (Edwards et al. 2001). Another urban exposure project in Camden, USA, found that ambient concentrations of polycyclic aromatic hydrocarbons (PAH), from traffic emissions and industrial combustion, explained 44–96 % of variability in personal exposures (Zhu et al. 2011). We can therefore be fairly confident that, in the absence of significant indoor and/or occupational sources, ambient data can be used in personal exposure estimation to obtain meaningful results. Much of the remaining variability for these studies is generally explained by exposures while commuting.

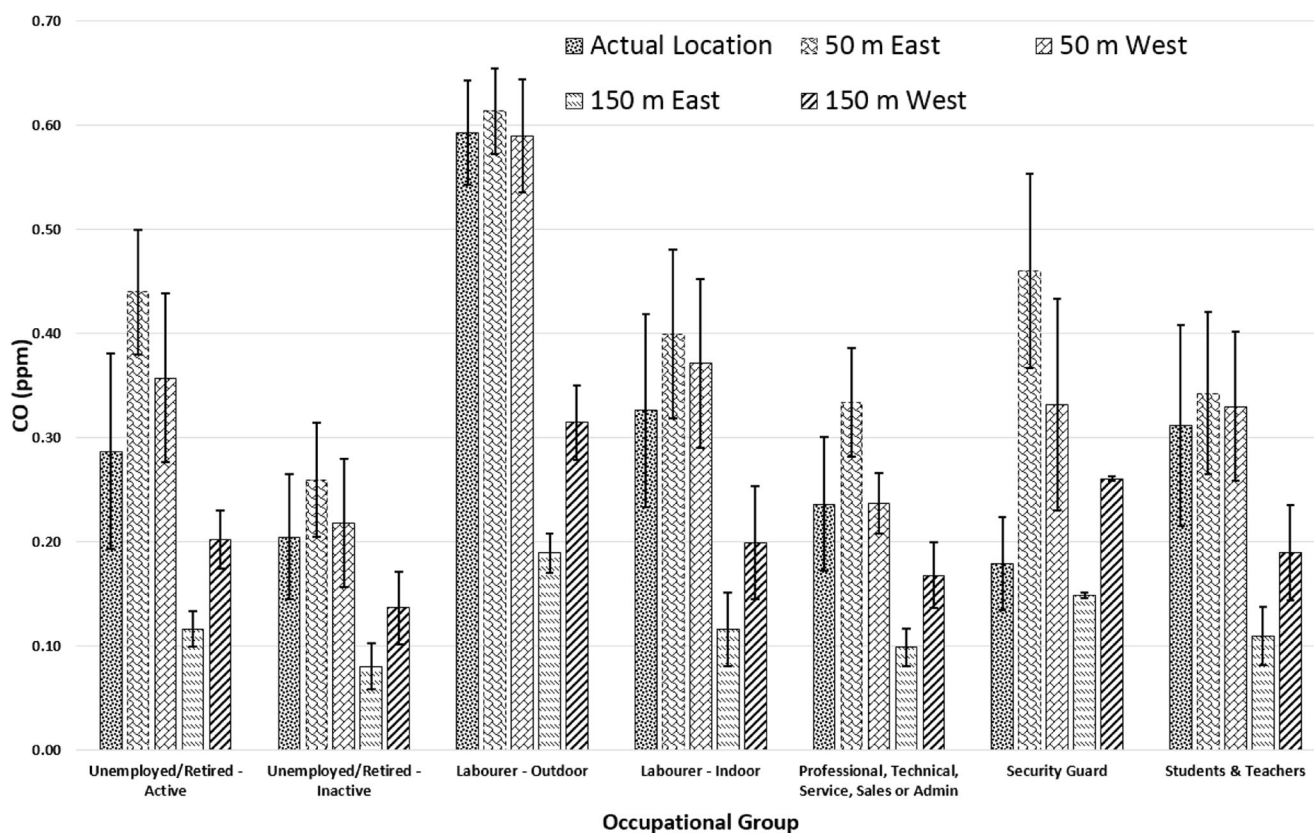


Fig. 6 Simulated total mean ambient CO exposure by occupational group for the month of July, 2010. Error bars denote 95 % confidence limits

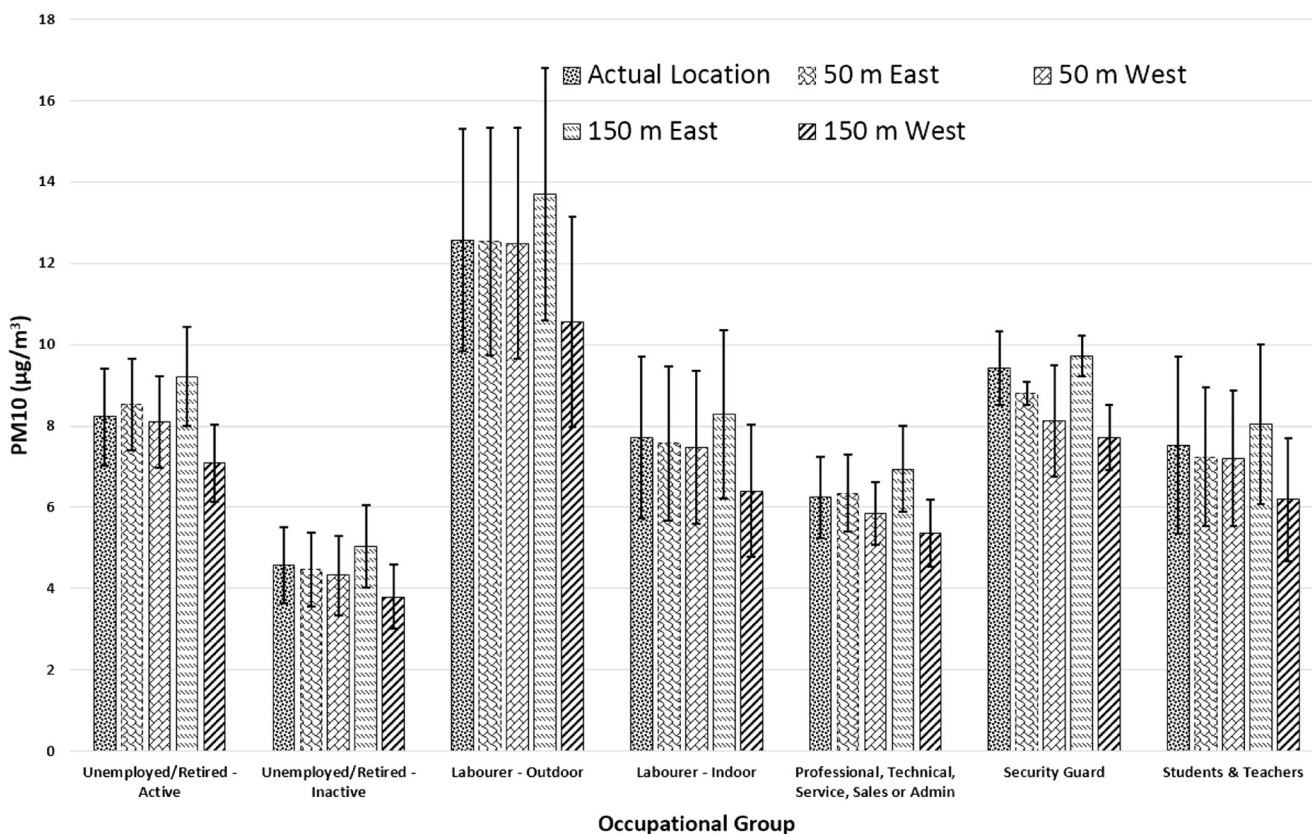


Fig. 7 Simulated total mean ambient PM₁₀ exposure by occupational group for the month of July, 2010. Error bars denote 95 % confidence limits

A further outcome from our analysis is that we have gained an indication of how differing occupation profiles would

potentially benefit from the >100 m roadway separation recommended by recent literature (Barros et al. 2013; Hystad

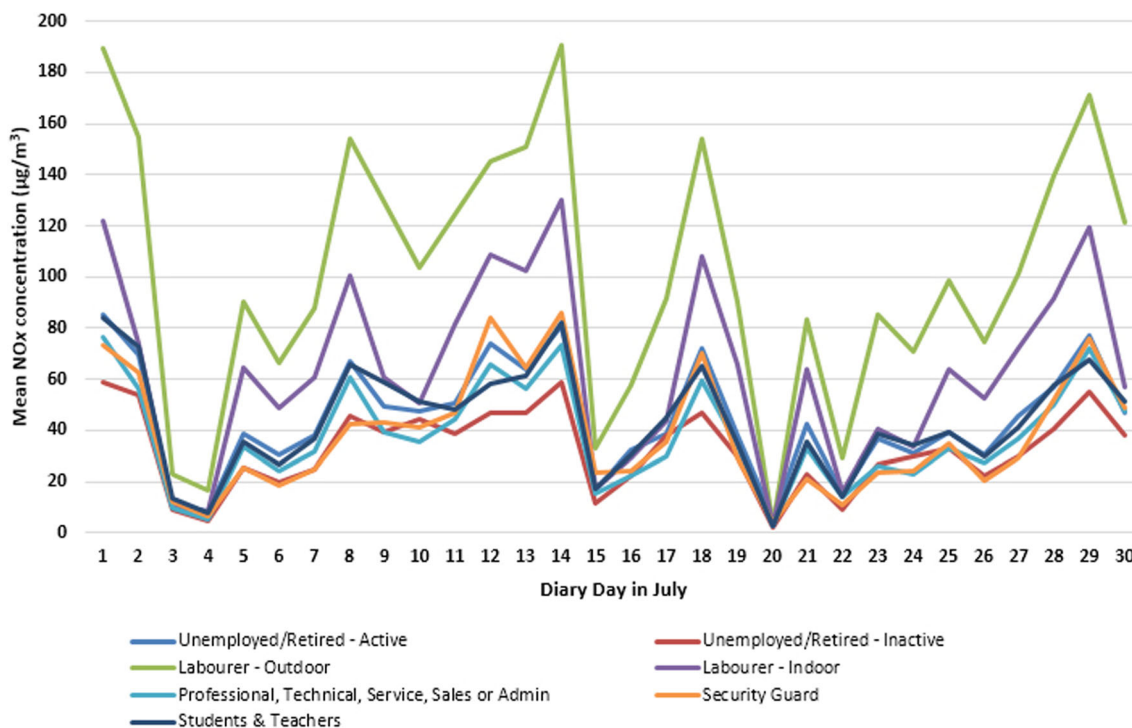


Fig. 8 Variation in simulated daily mean NO_x exposure by occupational group for the month of July, 2010

Table 5 GLM multivariate tests: proximity to highway and work location

	Test	Value	<i>F</i>	Effect- <i>df</i>	Error- <i>df</i>	<i>p</i> value
Intercept	Wilks	0.11	581	3	213	<0.001
Proximity/position	Wilks	0.29	26	12	564	<0.001
Work location	Wilks	0.48	10	18	603	<0.001
Proximity/position × work location	Wilks	0.79	1	72	637	0.96

et al. 2013). Likely owing to the weaker presence of northeast winds blowing toward the leeward side (27 % of all observations), increasing the separation of the group from 50–100 m was only significant ($p < 0.05$) at the windward side (downwind for 58 % of hourly observations, Fig. 1). The mean decrease downwind was 56 % (NO_x) and 71 % (CO) for the group and some occupations benefited more than others, but not by a great margin (5–7 %).

Perhaps a more important finding is that the unemployed/retired-active and security guard groups, who spent a large proportion of time outdoors and near traffic sources, would face a substantially increased exposure burden if living within the downwind corridor than if living elsewhere. Those working in ventilated offices, who spend less time outdoors for work and/or recreation, are afforded better long-term protection from ambient air. This is indicated by the results for those working in the CBD area (Grafton), who spent 8 h of each weekday inside mechanically ventilated office buildings. Despite being in the most polluted area (an inner-city street canyon), NO_x exposure was lower than for those who worked at four (out of six) alternative locations, in different environments (Fig. 9). This finding is supported by previous micro-environmental comparisons for office workers in Los Angeles, USA (Fujita et al. 2014) and Hertfordshire, UK (Kornartit et al. 2010). Comparatively, those working near traffic or outside are faced with higher exposure both during the day and then again when at home, especially if active with gardening and recreation in the evenings and during week-ends. Gardening or tinkering in the yard was a regular activity for two thirds of our unemployed/retired-active participants. For our security guards, both were positioned outdoors near busy roads. All occupations which involved spending a lot of time outside and/or near traffic resulted in higher exposure profiles than the unemployed/retired-inactive group, whose members collectively spent 85 % of their time indoors at home (Fig. 8).

Table 6 Whole model *R*: proximity to highway and work location

	Multiple- <i>R</i>	SS-model	<i>df</i> -Model	MS-model	SS-residual	<i>df</i> -Residual	MS-residual	<i>F</i>	<i>p</i> value
NO_x	0.771	83694.6	34	2461.6	57064.1	215	265.4	9.3	<0.001
CO	0.773	3.2	34	0.1	2.1	215	0.0	9.7	<0.001
PM_{10}	0.619	762.5	34	22.4	1227.4	215	5.7	3.9	<0.001

Recent exposure modeling studies

Moving away from population-based, citywide (mesoscale) simulations which utilize generated emissions data and/or proxy variable inputs, is likely to substantially improve the accuracy of personal exposure estimates. These individual results can thereafter be collated to build results for a wider population, which can form a stronger basis for epidemiological studies. One example originates from Münster, Germany, where researchers kriged ambient and local particulate concentrations over a 250-m² citywide grid, included GPS time-activity data, indoor emission sources, and indoor/outdoor ratios for transport microenvironments, achieving strong correlations between modeled and measured exposures (Gerharz et al. 2013).

An NO_2 study using LUR methods in Antwerp, Belgium, found a mean exposure range of 11–36 $\mu\text{g}/\text{m}^3$ (Dons et al. 2014b). Assuming a kerbside NO_2/NO_x ratio of 31 % (Wang et al. 2011), the estimated NO_2 portion for our roadside corridor mean individual exposures would closely match this range at 9–31 $\mu\text{g}/\text{m}^3$ NO_2 or 29–104 $\mu\text{g}/\text{m}^3$ NO_x (Appendix 7). A mixed-method study trialing a range of kriging and regression modeling techniques in the UK calculated population mean results of 54–70 $\mu\text{g}/\text{m}^3$ for Blackpool and Manchester, respectively (Hannam et al. 2013). The best of these performed fairly well against results from personal passive samplers ($r = 0.60$ – 0.62). Further research in Hillsborough County, FL, USA, utilizing data generated by the CALPUFF dispersion model, eventuated in an urban residential group mean exposure of 22 $\mu\text{g}/\text{m}^3$ and individual exposures up to 43 $\mu\text{g}/\text{m}^3$ (Gurram et al. 2014). The collective results from these NO_x studies are reasonably comparable to our group means of 25–60 $\mu\text{g}/\text{m}^3$ (Table 2, Appendix 7).

To our knowledge, only one publication has specifically applied APEX to a study population, in Atlanta, GA, USA (Dionisio et al. 2013). Although individual profiles were simulated, only median results at the zip code level were

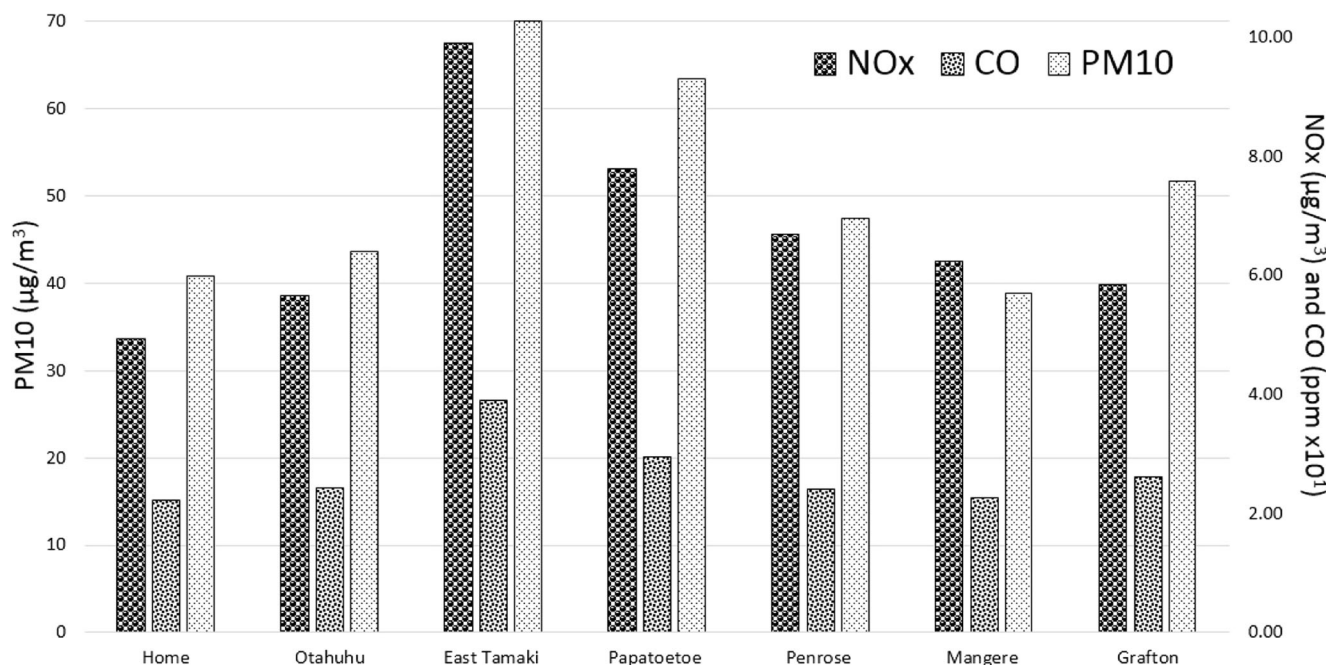


Fig. 9 Simulated mean ambient pollutant exposure by work location for the month of July, 2010

provided. While not directly comparable, median NO_x concentrations were 0.05 ppm or $\sim 94 \mu\text{g}/\text{m}^3$ (based on the molecular weight of NO_2) and CO 0.80 ppm, considerably greater than our mean exposures, which is explained by higher ambient concentrations in Atlanta. The authors noted good agreement between median zip code APEX results and associated central site monitors even though there was substantial spread between the lower and upper 95th percentiles.

Study limitations and recommendations

The limitations within the current study are not dissimilar to those faced by previous work, with all presenting clear strengths and weaknesses. The main criticism of our work is that we used a limited sample size ($n=51$), which may be statistically representative of the wider population, especially when comparing occupational groups with as few as just two members. However, smaller sample sizes are typical of this type of modeling due to the resource-intensive nature of collecting detailed time-activity data (Chatzis et al. 2005; Dias and Tchepel 2014; Gerharz et al. 2013).

Further limitations, which very few studies adequately address, include the inability to account for exposures while commuting and indoor sources at the home, as well as the lack of model validation.

The challenges associated with including commute-time exposure and indoor resident-specific sources are widely acknowledged and improvements are ongoing (Dias and Tchepel 2014; Vette et al. 2013). Exposure while commuting is currently best handled by in-traffic exposure models (Dons et al. 2014a) or LUR models that include traffic volumes/road

source intensity. The inclusion of indoor sources and commuting exposure continues to be completely omitted from some projects due to associated complexities (Dons et al. 2014b; Stroh et al. 2012).

The validation of our results would only have been possible if we had the ability to sample in microenvironments with no indoor sources. This is unrealistic in the context of personal sampling where dust resuspension from human activity and emissions from cooking activity and home heating cannot be completely eliminated. Therefore, it is appropriate to omit validation in ambient modeling studies with an absence of controlled microenvironments as the results are useful in the epidemiological analysis of health effects where ambient sources are the primary interest (Dionisio et al. 2013).

Despite all of the limitations mentioned herein, our results do not deviate wildly from the ranges found in previous modeling studies (Gurram et al. 2014; Hannam et al. 2013; Zidek et al. 2005). Finally, a larger population sample would have likely strengthened statistical associations between occupational groups at the interaction effect level and improved estimates of potential exposure benefits when moving further away from the highway.

Our study has provided an interesting insight into the exposures of near-roadway residents in South Auckland and contains some meaningful results, regardless of its limitations. It is a good “first look” at personal exposure simulations for a New Zealand city and provides the foundation for future local studies, which could be expanded to focus on particular population subsets. Additionally, this unique application of a personal exposure model may help inform other highway proximity population exposure assessments in the context of time-

activity patterns altering exposure. These findings are especially useful for groups and individuals with pre-existing health conditions and for those who work in occupations where exposure to traffic pollution is already high. Developing an understanding of who is affected most by near-highway living, may help steer local land use policy in a direction that aims to protect the most vulnerable citizens. Future analyses could include sociodemographics such as age and ethnicity, combined with health status data, i.e., susceptible individuals.

Such an application has the potential to inform epidemiological studies, as demonstrated by previous work, e.g., Sarnat et al. (2013).

Acknowledgments This work was made possible as a result of research conducted by the National Institute of Water and Atmospheric Research (NIWA), under New Zealand Transport Agency (NZTA) funding - project 476 TAR09/18. We would also like to thank the Auckland Council for providing air quality data at the Penrose and Grafton sites.

Appendices

Appendix 1

Table 7 Parameters used to calculate the distribution shapes for APEX participant microenvironments (provided in Appendix 3)

Indoor environment	Distribution shape	Parameter1 Geometric mean	Parameter2 Geometric standard deviation	Lower truncation limit	Upper truncation limit	Resample outside truncation? (Y/N)
Residence	Lognormal	1.657	1.334	0.1	10	Y
Office building, bank, post office	Lognormal	1.109	3.015	0.07	13.8	Y
Grocery store, Convenience store	Lognormal	1.109	3.015	0.07	13.8	Y
Shopping mall, nongrocery store	Lognormal	1.109	3.015	0.07	13.8	Y
Restaurant	Lognormal	1.109	3.015	0.07	13.8	Y
Bar, night club, café	Lognormal	1.109	3.015	0.07	13.8	Y
School	Discrete ^a	0.8, 1.3, 1.8, 2.19, 2.2, 2.21, 3.0	N/A	N/A	N/A	
Community center or auditorium	Lognormal	1.109	3.015	0.07	13.8	Y
Hospital, medical care facility	Lognormal	1.109	3.015	0.07	13.8	Y
Industrial, factory, warehouse	Normal	0.70	0.20	0.1	1.0	Y
Other indoor	Lognormal	1.109	3.015	0.07	13.8	Y
Outdoor environment	Distribution	Parameter1 Mean	Parameter2 Standard deviation	Lower truncation limit	Upper truncation limit	Resample outside truncation?
Residential	Point ^b	N/A				
Other outdoor non-residential	Point					
Park or golf course	Point					
Boat	Normal	0.70	0.20	0.1	1.0	Y

^a This type of distribution has no parameters; it contains a list of up to 100 discrete values. The distribution returns each of these values with equal probability. For a complete list of default parameters for air exchange rates, decay rates, penetration factors and proximity factors, refer to the APEX model documentation (EPA 2012a, b)

^b This type of distribution uses the “Factors” method, where a proximity factor is used to calculate the concentration value at a specific location. This accounts for local meteorological influences on dispersion, as a function of distance from the nearest ambient monitor

Appendix 2

Table 8 Example of APEX time-activity input for an indoor laborer (descriptions in parentheses)

Diary day	Time	Duration	Activity	(Activity)	Location	(Microenvironment)
diaryP06_day3	0500	30	14500	Sleep	30125	Bedroom-home residence
diaryP06_day3	0530	30	14400	Eat	30121	Kitchen-home residence
diaryP06_day3	0600	60	10000	Work	32200	Industrial/factory/warehouse

Appendix 3

Table 9 Types of model inputs, microenvironments, and methods used to estimate concentrations

Model input file	APEX filename	Function	
Districts file	air_districts	Maps the coordinates and radii of each study zone (refer to Fig. 2), which is represented by a central air quality monitor	
Sectors file	pop_geo	Maps the coordinates of the local sectors in which the population resides. In our application, each sector represents an individual's home, rather than a census unit or wider regional area	
Air quality data files	NOx_concs, CO_concs, etc.	Provides hourly mean pollutant concentrations at each air monitor Nitrogen oxides, carbon monoxide, and particulate matter <10 μm	
Meteorology file	METdata	Provides hourly mean meteorological data at each air monitoring site. Temp, humidity, precipitation, wind speed, and direction	
Zones file	METSites	Maps the coordinates of each meteorological site (identical to those in the air districts file)	
Microenvironments file	ME_descriptions	Provides parameters for microenvironment infiltration and decay (see Appendix 2)	
Population file	Pop	Maps the coordinates of the resident population [same as sectors]	
Occupations file	Occ	Matches individual diary days to specific occupations [and work locations]	
Functions file	ProfileFunctions	Selects diary days depending on variables such as temperature	
Profile file	ProfileFactors	Assigns a population of one individual to each sector in the sectors file	
DiaryQuest file	Quest	Provides personal data from local time-activity survey (e.g., ethnicity, age, occupation). As exposure was not dependent on these most of these variables, only occupation was used in our application.	
DiaryEvent file	Events	Provides activity and microenvironment location data for time-activity diary day in 15, 30, 45, and 60-min blocks (see Appendix 2)	
Participant diary environments	APEX Microenvironment	Method ^a	Parameter type
Indoor			
Participant's home address, or friend or family member's home	Indoor-residence	Mass Balance	Air exchange rate
Community centers and auditoriums	Indoor-community center	Mass Balance	Air exchange rate
Restaurants	Indoor-Restaurant	Mass Balance	Air exchange rate
Office buildings, banks, post offices	Indoor-Office building	Mass Balance	Air exchange rate
Bars, nightclubs, cafés	Indoor-bar night club café	Mass Balance	Air exchange rate
Schools	Indoor-school	Mass Balance	Air exchange rate
Shopping malls and other large stores	Indoor-shopping mall	Mass Balance	Air exchange rate
Grocery and convenience stores	Indoor-grocery store	Mass Balance	Air exchange rate
Hospitals and medical facilities	Indoor-hospital	Mass Balance	Air exchange rate

Table 9 (continued)

Outdoor			
Participant's home address, or friend or family member's home	Outdoor-residential	Factors	Proximity
Other nonresidential	Other outdoor nonresidential	Factors	Proximity
Parks and recreational areas	Outdoor-park or golf course	Factors	Proximity
Boats	Outdoor-boat	Factors	Proximity
Participant occupational environments	APEX microenvironment	Method ^a	Parameter type
Unemployed/retired	Indoor-residence	Mass Balance	Air exchange rate
Laborer-outdoor	Outdoor-residential	Factors	Proximity
Laborer-indoor	Indoor-industrial, factory, warehouse	Mass Balance	Air exchange rate
Prof./tech. etc.	Indoor-office building	Mass Balance	Air exchange rate
Security	Mixed indoor-industrial and outdoor	Mixed	Air exchange rate and proximity
Students/teachers	Indoor-school	Mass Balance	Air exchange rate

^a The mass balance method calculates concentrations in a microenvironment (ME) based on the ME concentration in the previous time step and the inflow to and outflow from the ME, by solving a differential equation that conserves the overall mass of the pollutant. In the factors model, the value of the concentration in a ME is not dependent on the concentration during the previous time step but applies stochastic factors to the ambient concentration to calculate the ME concentration. For example, a proximity factor can be used to adjust for expected differences between the concentrations at a monitor and the ambient concentrations outside the ME in question. For this application, proximity factors are set to 1. A more detailed description of these models, as they are implemented in APEX, is provided in the APEX documentation (EPA 2012a, b)

Appendix 4

Table 10 Percentage of time population spent engaging in activities, grouped by occupation

Activity	Unemployed/ retired-active (<i>n</i> =9)	Unemployed/ retired-inactive (<i>n</i> =12)	Laborer–outdoor (<i>n</i> =2)	Laborer–indoor (<i>n</i> =10)	Professional, technical, service, sales, or admin (<i>n</i> =12)	Security guards (<i>n</i> =3)	Students and teachers (<i>n</i> =3)	Study population total (<i>n</i> =51)
Paid work	0.0	2.4	22.6	21.3	21.3	24.2	9.5	13.3 ^a
General household activities	12.5	25.3	6.9	14.4	9.7	13.2	15.2	15.0
Outdoor chores and home hobbies	25.6	2.3	4.9	2.4	1.5	0.0	6.9	6.2
Child care	2.1	9.0	0.0	2.1	5.0	0.0	0.0	4.1
Shopping, errands	1.3	2.2	2.5	1.3	2.0	2.1	0.0	1.6
Eating	5.9	7.4	9.1	7.8	9.6	5.4	9.3	7.9
Sleeping or resting	38.2	40.6	38.6	38.1	37.2	37.1	36.2	38.0
Attending school or university	0.0	0.0	0.0	0.0	0.0	0.0	13.4	0.7
General entertainment, social activities	0.2	2.6	0.8	1.1	2.0	1.6	1.2	1.5
Social, political or religious activities	5.2	3.4	1.2	1.9	1.1	4.0	2.2	2.6
Participating in sports	1.1	0.0	1.4	1.2	1.0	0.0	2.1	0.8
Hunting, fishing, hiking	0.0	0.0	1.1	1.2	0.2	0.0	0.0	0.5
Passive, sitting (in-vehicle)	3.9	1.8	7.5	5.0	6.5	11.9	2.3	4.9
Walking or cycling	1.0	1.1	2.1	1.3	2.6	0.5	1.8	1.8
Other exercise and outdoor recreation	3.0	2.1	1.5	1.1	0.2	0.1	0.0	1.0

^a From a total of 28 workers, 5 were employed part-time. The remainder were either unemployed or retired (*n*=21), or secondary/university students (*n*=2). This led to a lower total percentage of time spent in paid work than percentages typically found in larger urban sample sizes

Appendix 5

Table 11 Percentage of time population spent in different environments, grouped by occupation

Environment	Unemployed/ retired-active (<i>n</i> =9)	Unemployed/ retired-inactive (<i>n</i> =12)	Laborer- outdoor (<i>n</i> =2)	Laborer- indoor (<i>n</i> =10)	Professional, technical, service, sales, or admin (<i>n</i> =12)	Security guards (<i>n</i> =3)	Students and teachers (<i>n</i> =3)	Study population total (<i>n</i> =51)
Residence, indoor	58.1	84.5	57.0	63.0	59.0	54.4	66.7	64.8
Residence, outdoor	25.7	17.3	6.1	2.9	1.7	0.0	6.9	6.5
Other residence, indoor	0.4	14.5	0.0	0.3	1.1	3.5	0.0	1.0
Other residence, outdoor	3.8	3.5	26.2	0.2	0.5	4.4	0.6	2.1
Car ^a	3.7	8.8	3.4	2.8	3.1	10.9	2.3	4.4
Bus ^a	0.0	0.5	0.0	0.0	0.5	0.0	0.0	0.7
Boat	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.1
Outdoor, local suburb	0.3	17.3	0.0	0.8	0.2	0.0	1.4	0.9
Outdoor, other suburb	0.0	4.8	1.5	0.5	0.5	0.0	0.4	0.4
Nonresidence, indoor	0.8	15.0	0.0	1.1	5.4	0.0	0.0	2.0
Nonresidence, outdoor	0.0	0.5	0.0	0.3	0.0	8.5	0.0	0.5
Office building, bank, post office	0.0	0.0	0.0	0.0	8.3	0.0	0.0	1.9
Industrial, factory, warehouse	0.0	0.0	0.0	21.2	4.5	9.6	0.0	5.9
Grocery, convenience store	0.8	4.5	0.6	0.4	0.2	0.1	0.0	0.5
Shopping mall, non-grocery store	0.2	2.3	1.3	0.5	2.0	2.0	0.0	0.8
Bar, night club, bowling alley	0.0	0.0	0.0	0.4	0.6	2.4	1.6	0.5
Indoor gym, health club	1.5	0.0	0.0	0.0	2.1	0.6	0.0	0.9
Childcare facility	0.0	0.0	0.0	0.0	1.7	0.0	0.0	0.4
Auditorium, arena, concert hall	0.1	0.0	0.0	0.3	0.3	0.0	0.0	0.2
Laundromat	0.0	0.0	0.0	1.6	0.0	0.0	0.0	0.3
Hospital, medical care facility	0.0	0.0	0.0	0.0	2.1	0.0	0.0	0.5
School	0.0	0.0	0.0	0.0	3.7	0.0	15.0	1.7
Restaurant	0.3	1.0	0.0	0.3	0.1	1.3	0.0	0.2
Church	0.7	0.0	0.8	0.7	0.0	0.5	0.0	0.3
Public playground	2.9	4.7	0.0	0.2	0.3	0.0	3.9	0.9
Public park	0.4	9.3	2.0	1.4	1.4	0.0	1.4	1.1
Pool, river, lake	0.3	0.0	1.2	0.6	0.5	1.8	0.0	0.7

^a Although these values were included from the time-activity diaries, they were not used in the exposure model. These missing periods within the model, typically consisting of a 15-30-min commute, were replaced by the preceding environment, i.e., an extra 15–30 min within the home (a.m.) or work environment (p.m.) were assigned

Appendix 6

Table 12 Variables used for GLM analysis and APEX microenvironments assigned to occupations

Variable	Variable type	Units	Example input
Main effects	Independent		
Proximity/position	Categorical	Meters and position relative to wind direction	50 downwind, 150 downwind
Occupational group	Categorical	Group name	Professional/Technical, Teacher/Student
Work location	Categorical	Location name	Penrose, Grafton
Pollutants	Dependent		
NO _x	Continuous	µg/m ³	Integer
CO	Continuous	ppm	Integer
PM ₁₀	Continuous	µg/m ³	Integer

Appendix 7

Table 13 Summary NO_x (µg/m³) statistics from APEX output

Actual Location	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	% Change From		
Unemployed/Retired - Active	9	270	44.6	32.7	1.4	148.8	34.2	3.9	-		
Unemployed/Retired - Inactive	12	360	27.9	20.8	0.6	105.0	23.3	2.1	-		
Labourer - Outdoor	2	60	101.0	51.5	2.5	215.0	94.9	13.0	-		
Labourer - Indoor	10	300	63.3	44.6	1.2	228.9	60.5	5.1	-		
Professional, Technical, Service, Sales or Admin	9	270	38.0	28.7	1.5	141.1	31.1	3.4	-		
Security Guard	2	60	38.6	24.2	3.2	99.4	32.3	6.1	-		
Students & Teachers	6	180	44.2	31.6	1.2	148.1	40.1	4.6	-		
Group Total	50	1500	45.1	36.9	0.6	228.9	34.3	1.9			
50 m Downwind (east)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc		
Unemployed/Retired - Active	9	270	65.6	35.9	1.1	148.8	66.7	4.3	47		
Unemployed/Retired - Inactive	12	360	36.8	22.1	0.5	122.4	35.5	2.3	32		
Labourer - Outdoor	2	60	104.2	52.5	2.5	216.2	97.6	13.3	3		
Labourer - Indoor	10	300	74.6	49.6	1.2	232.6	72.0	5.6	18		
Professional, Technical, Service, Sales or Admin	9	270	52.4	33.2	0.4	147.9	49.8	4.0	38		
Security Guard	2	60	74.7	39.9	2.2	162.2	71.2	10.1	93		
Students & Teachers	6	180	53.1	37.9	0.6	178.3	47.1	5.6	20		
Group Total	50	1500	59.2	41.1	0.4	232.6	53.3	2.2	31		
50 m Upwind (west)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc	50 m East	
Unemployed/Retired - Active	9	270	52.1	32.6	2.7	134.5	51.2	3.9	17	-21	
Unemployed/Retired - Inactive	12	360	29.3	23.1	0.6	110.4	22.8	2.4	5	-21	
Labourer - Outdoor	2	60	100.1	51.2	3.6	215.0	94.9	13.0	-1	-4	
Labourer - Indoor	10	300	69.5	47.1	1.8	228.9	65.8	5.3	10	-7	
Professional, Technical, Service, Sales or Admin	9	270	35.4	22.9	1.9	113.5	29.6	2.7	-7	-32	
Security Guard	2	60	50.7	33.6	7.3	155.0	42.4	8.5	31	-32	
Students & Teachers	6	180	45.9	28.6	1.2	138.3	42.0	4.2	4	-14	
Group Total	50	1500	48.5	38.8	0.6	228.9	38.8	2.1	7	-18	
150 m Downwind (east)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc	50 m East	
Unemployed/Retired - Active	9	270	27.6	18.6	1.1	87.6	23.7	2.2	-38	-58	
Unemployed/Retired - Inactive	12	360	16.5	12.5	0.6	66.2	12.4	1.3	-41	-55	
Labourer - Outdoor	2	60	49.1	31.3	3.4	111.9	36.9	7.9	-51	-53	
Labourer - Indoor	10	300	33.2	27.5	1.0	124.1	24.8	3.1	-48	-56	
Professional, Technical, Service, Sales or Admin	9	270	23.3	17.6	0.5	87.7	18.5	2.1	-39	-55	
Security Guard	2	60	35.4	23.4	3.2	95.2	27.9	5.9	-8	-53	
Students & Teachers	6	180	23.7	20.2	0.8	97.7	17.7	3.0	-46	-55	
Group Total	50	1500	26.3	22.0	0.5	124.1	20.5	1.2	-42	-56	
150 m Upwind (west)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc	50 m East	150 m East
Unemployed/Retired - Active	9	270	26.2	16.9	2.7	90.9	22.9	2.0	-41	-50	-5
Unemployed/Retired - Inactive	12	360	15.7	12.0	2.4	80.8	12.2	1.2	-44	-46	-5
Labourer - Outdoor	2	60	47.2	30.5	12.7	137.0	40.6	7.7	-53	-53	-4
Labourer - Indoor	10	300	31.6	26.1	2.7	158.3	23.8	3.0	-50	-54	-5
Professional, Technical, Service, Sales or Admin	9	270	22.4	16.5	1.8	84.4	17.7	2.0	-41	-37	-4
Security Guard	2	60	33.8	21.4	9.4	102.0	28.9	5.4	-12	-33	-4
Students & Teachers	6	180	23.3	19.6	2.4	112.4	16.8	2.9	-47	-49	-2
Group Total	50	1500	25.1	20.8	1.8	158.3	18.5	1.1	-44	-48	-4

Significant differences between groups ($p < 0.05$) are indicated in red

Appendix 8

Table 14 Summary CO (ppm) statistics from APEX output

Actual Location	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	% Change From		
Unemployed/Retired - Active	9	270	0.29	0.22	0.00	0.98	0.23	0.03	-		
Unemployed/Retired - Inactive	12	360	0.18	0.13	0.00	0.67	0.15	0.01	-		
Labourer - Outdoor	2	60	0.59	0.31	0.03	1.25	0.55	0.08	-		
Labourer - Indoor	10	300	0.33	0.25	0.01	1.32	0.31	0.03	-		
Professional, Technical, Service, Sales or Admin	9	270	0.24	0.18	0.00	0.85	0.20	0.02	-		
Security Guard	2	60	0.18	0.13	0.00	0.47	0.17	0.03	-		
Students & Teachers	6	180	0.31	0.22	0.00	0.91	0.29	0.03	-		
Group Total	50	1500	0.27	0.22	0.00	1.32	0.22	0.01			
50 m Downwind (east)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc		
Unemployed/Retired - Active	9	270	0.44	0.25	0.01	1.03	0.45	0.03	53		
Unemployed/Retired - Inactive	12	360	0.25	0.16	0.01	0.80	0.23	0.02	42		
Labourer - Outdoor	2	60	0.61	0.32	0.03	1.29	0.58	0.08	4		
Labourer - Indoor	10	300	0.40	0.27	0.01	1.35	0.38	0.03	22		
Professional, Technical, Service, Sales or Admin	9	270	0.33	0.21	0.00	0.91	0.31	0.02	41		
Security Guard	2	60	0.46	0.25	0.02	1.11	0.45	0.06	157		
Students & Teachers	6	180	0.38	0.25	0.01	1.17	0.34	0.04	23		
Group Total	50	1500	0.37	0.25	0.00	1.35	0.33	0.01	36		
50 m Upwind (west)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc	50 m East	
Unemployed/Retired - Active	9	270	0.36	0.24	0.02	1.03	0.32	0.03	25	-19	
Unemployed/Retired - Inactive	12	360	0.19	0.14	0.01	0.71	0.18	0.01	10	-22	
Labourer - Outdoor	2	60	0.59	0.31	0.03	1.25	0.55	0.08	0	-4	
Labourer - Indoor	10	300	0.37	0.25	0.02	1.32	0.34	0.03	14	-7	
Professional, Technical, Service, Sales or Admin	9	270	0.24	0.15	0.01	0.82	0.21	0.02	0	-29	
Security Guard	2	60	0.33	0.20	0.05	0.90	0.30	0.05	85	-28	
Students & Teachers	6	180	0.34	0.20	0.02	0.91	0.32	0.03	11	-10	
Group Total	50	1500	0.31	0.22	0.01	1.32	0.26	0.01	13	-17	
150 m Downwind (east)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc	50 m East	
Unemployed/Retired - Active	9	270	0.12	0.11	0.0	0.44	0.08	0.01	-59	-74	
Unemployed/Retired - Inactive	12	360	0.08	0.08	0.0	0.42	0.06	0.01	-57	-69	
Labourer - Outdoor	2	60	0.19	0.16	0.0	0.54	0.15	0.04	-68	-69	
Labourer - Indoor	10	300	0.12	0.12	0.0	0.78	0.07	0.01	-65	-71	
Professional, Technical, Service, Sales or Admin	9	270	0.10	0.09	0.0	0.41	0.07	0.01	-58	-70	
Security Guard	2	60	0.15	0.12	0.0	0.43	0.14	0.03	-17	-68	
Students & Teachers	6	180	0.11	0.11	0.0	0.48	0.08	0.02	-63	-70	
Group Total	50	1500	0.11	0.11	0.00	0.78	0.07	0.01	-60	-71	
150 m Upwind (west)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc	50 m West	150 m East
Unemployed/Retired - Active	9	270	0.20	0.13	0.02	0.70	0.17	0.02	-29	-43	74
Unemployed/Retired - Inactive	12	360	0.13	0.10	0.01	0.61	0.10	0.01	-26	-33	70
Labourer - Outdoor	2	60	0.31	0.19	0.07	1.02	0.28	0.05	-47	-47	66
Labourer - Indoor	10	300	0.20	0.16	0.01	1.23	0.15	0.02	-39	-46	72
Professional, Technical, Service, Sales or Admin	9	270	0.17	0.12	0.02	0.78	0.13	0.01	-29	-29	70
Security Guard	2	60	0.26	0.18	0.05	0.90	0.23	0.04	45	-22	75
Students & Teachers	6	180	0.20	0.14	0.02	0.82	0.16	0.02	-35	-41	78
Group Total	50	1500	0.18	0.14	0.01	1.23	0.14	0.01	-31	-40	72

Significant differences between groups ($p < 0.05$) are highlighted in red

Appendix 9

Table 15 Summary PM₁₀ (µg/m³) statistics from APEX output

Actual Location	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	% Change From		
Unemployed/Retired - Active	9	270	8.2	3.6	1.0	20.6	7.7	0.4	-		
Unemployed/Retired - Inactive	12	360	4.4	2.3	0.4	15.2	4.0	0.2	-		
Labourer - Outdoor	2	60	12.6	5.2	2.1	25.2	12.3	1.3	-		
Labourer - Indoor	10	300	7.7	4.5	0.8	27.1	6.8	0.5	-		
Professional, Technical, Service, Sales or Admin	9	270	6.2	2.9	0.8	15.5	6.1	0.3	-		
Security Guard	2	60	9.4	3.5	3.6	22.4	9.1	0.9	-		
Students & Teachers	6	180	6.9	3.7	0.6	19.5	6.2	0.1	-		
Group Total	50	1500	6.9	4.0	0.4	27.1	6.2	0.4	-		
50 m Downwind (east)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc		
Unemployed/Retired - Active	9	270	8.5	3.8	1.0	20.6	8.3	0.5	4		
Unemployed/Retired - Inactive	12	360	4.2	2.2	0.3	14.9	4.0	0.2	-3		
Labourer - Outdoor	2	60	12.5	5.3	2.0	26.0	12.1	1.3	0		
Labourer - Indoor	10	300	7.6	4.5	0.8	27.1	6.6	0.5	-2		
Professional, Technical, Service, Sales or Admin	9	270	6.3	3.1	0.5	15.7	6.1	0.4	2		
Security Guard	2	60	8.8	3.7	1.9	21.9	8.7	0.9	-7		
Students & Teachers	6	180	6.8	3.7	0.6	19.5	6.2	0.5	-2		
Group Total	50	1500	6.9	4.1	0.3	27.1	6.1	0.3	-1		
50 m Upwind (west)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc	50 m East	
Unemployed/Retired - Active	9	270	8.1	3.5	1.0	20.6	7.8	0.4	-1	-5	
Unemployed/Retired - Inactive	12	360	4.0	2.1	0.3	15.4	3.8	0.2	-8	-5	
Labourer - Outdoor	2	60	12.5	5.2	2.1	25.2	12.2	1.3	-1	0	
Labourer - Indoor	10	300	7.5	4.3	0.8	27.1	6.5	0.5	-3	-1	
Professional, Technical, Service, Sales or Admin	9	270	5.8	2.6	0.7	14.6	5.7	0.3	-6	-8	
Security Guard	2	60	8.1	3.4	2.0	21.6	7.8	0.9	-14	-8	
Students & Teachers	6	180	6.7	3.4	0.6	19.5	6.2	0.5	-4	-1	
Group Total	50	1500	6.6	3.9	0.3	27.1	5.9	0.3	-5	-4	
150 m Downwind (east)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc	50 m East	
Unemployed/Retired - Active	9	270	9.2	3.7	1.8	22.8	9.1	0.4	12	8	
Unemployed/Retired - Inactive	12	360	4.8	2.4	0.6	16.4	4.4	0.3	9	13	
Labourer - Outdoor	2	60	13.7	5.1	4.0	28.6	13.2	1.3	9	9	
Labourer - Indoor	10	300	8.3	4.6	1.6	30.2	7.2	0.5	7	9	
Professional, Technical, Service, Sales or Admin	9	270	6.9	3.1	1.1	17.4	6.7	0.4	11	9	
Security Guard	2	60	9.7	3.5	3.6	22.4	9.7	0.9	3	10	
Students & Teachers	6	180	7.4	3.7	1.4	21.9	6.6	0.5	8	10	
Group Total	50	1500	7.5	4.2	0.6	30.2	6.8	0.4	9	10	
150 m Upwind (west)	N (persons)	N (days simulated)	Mean	SD	Min	Max	Median	95% CI	Actual Loc	50 m West	150 m East
Unemployed/Retired - Active	9	270	7.1	3.0	0.7	19.9	6.9	0.4	-14	-12	-23
Unemployed/Retired - Inactive	12	360	3.6	1.8	0.4	10.0	3.3	0.2	-18	-10	-25
Labourer - Outdoor	2	60	10.6	4.3	2.3	26.8	10.2	1.1	-16	-15	-23
Labourer - Indoor	10	300	6.4	3.8	0.7	25.3	5.5	0.4	-17	-14	-23
Professional, Technical, Service, Sales or Admin	9	270	5.4	2.5	0.9	14.5	5.2	0.3	-14	-8	-23
Security Guard	2	60	7.7	3.5	1.3	20.6	7.4	0.9	-18	-5	-21
Students & Teachers	6	180	5.8	3.1	0.8	16.9	5.3	0.5	-17	-14	-23
Group Total	50	1500	5.8	3.4	0.4	26.8	5.2	0.3	-16	-12	-23

Significant differences between groups ($p < 0.05$) are highlighted in red

References

- Auckland Council (2005) The ambient air quality monitoring network in the Auckland Region. Technical Publication No. 296. Auckland Regional Council, Auckland
- Barros N, Fontes T, Silva MP, Manso MC (2013) How wide should be the adjacent area to an urban motorway to prevent potential health impacts from traffic emissions? *Transp Res A Policy Pract* 50:113–128. doi:10.1016/j.tra.2013.01.021
- Bello A, Quinn M, Perry M, Milton D (2009) Characterization of occupational exposures to cleaning products used for common cleaning tasks—a pilot study of hospital cleaners. *Environ Health* 8:11. doi:10.1186/1476-069X-8-11
- Brugge D et al (2013) Highway proximity associated with cardiovascular disease risk: the influence of individual-level confounders and exposure misclassification. *Environ Health* 12:84. doi:10.1186/1476-069X-12-84
- Bullen C, Keams RA, Clinton J, Laing P, Mahoney F, McDuff I (2008) Bringing health home: householder and provider perspectives on the healthy housing programme in Auckland, New Zealand. *Soc Sci Med* 66:1185–1196. doi:10.1016/j.socscimed.2007.11.038
- Buonanno G, Stabile L, Morawska L (2014) Personal exposure to ultra-fine particles: the influence of time-activity patterns. *Sci Total Environ* 468–469:903–907. doi:10.1016/j.scitotenv.2013.09.016
- Butler S, Williams M, Tukuitonga C, Paterson J (2003) Problems with damp and cold housing among Pacific families in New Zealand. *NZ Med J* 116:1–8
- Chatzis C, Alexopoulos EC, Linos A (2005) Indoor and outdoor personal exposure to benzene in Athens, Greece. *Sci Total Environ* 349:72–80. doi:10.1016/j.scitotenv.2005.01.034
- Cheer T, Kearns R, Murphy L (2002) Housing policy, poverty, and culture: ‘discounting’ decisions among Pacific peoples in Auckland, New Zealand. *Environ Plan C Gov Policy* 20:497–516. doi:10.1068/c04r
- Delgado-Saborit JM, Aquilina NJ, Meddings C, Baker S, Harrison RM (2011) Relationship of personal exposure to volatile organic compounds to home, work and fixed site outdoor concentrations. *Sci Total Environ* 409:478–488. doi:10.1016/j.scitotenv.2010.10.014
- di Marco GS, Kephelopoulous S, Ruuskanen J, Jantunen M (2005) Personal carbon monoxide exposure in Helsinki, Finland. *Atmos Environ* 39:2697–2707
- Dias D, Tchepel O (2014) Modelling of human exposure to air pollution in the urban environment: a GPS-based approach. *Environ Sci Pollut Res* 21:3558–3571. doi:10.1007/s11356-013-2277-6
- Dionisio KL et al (2013) Development and evaluation of alternative approaches for exposure assessment of multiple air pollutants in Atlanta, Georgia. *J Expo Sci Environ Epidemiol* 23:581–592. doi:10.1038/jes.2013.59
- Dons E, Kochan B, Bellemans T, Wets G, Panis LI (2014a) Modeling personal exposure to air pollution with AB2C: environmental inequality. *Procedia Comput Sci* 32:269–276. doi:10.1016/j.procs.2014.05.424
- Dons E, Van Poppel M, Int Panis L, De Prins S, Berghmans P, Koppen G, Matheussen C (2014b) Land use regression models as a tool for short, medium and long term exposure to traffic related air pollution. *Sci Total Environ* 476–477:378–386. doi:10.1016/j.scitotenv.2014.01.025
- Edwards R, Jurvelin J, Saarela K, Jantunen M (2001) VOC concentrations measured in personal samples and residential indoor, outdoor and workplace microenvironments in EXPOLIS-Helsinki, Finland. *Atmos Environ* 35:4531–4543
- EPA 2012a 'Total Risk Integrated Methodology (TRIM) Air Pollutants Exposure Model Documentation (TRIM.Expo/APEX, Version 4.5) Volume 1: User's Guide'. U.S. Environmental Protection Agency, Durham
- EPA 2012b 'Total Risk Integrated Methodology (TRIM) Air Pollutants Exposure Model Documentation (TRIM.Expo/APEX, Version 4.5) Volume 2: Technical Support Document'. U.S. Environmental Protection Agency, Durham
- Favarato G, Anderson HR, Atkinson R, Fuller G, Mills I, Walton H (2014) Traffic-related pollution and asthma prevalence in children. Quantification of associations with nitrogen dioxide. *Air Qual Atmos Health* 1–8. doi:10.1007/s11869-014-0265-8
- Fujita EM, Campbell DE, Arnott WP, Johnson T, Ollison W (2014) Concentrations of mobile source air pollutants in urban microenvironments. *J Air Waste Manage Assoc.* doi:10.1080/10962247.2013.872708
- Georgopoulos P et al (2009) Air quality modeling needs for exposure assessment from the source-to-outcome perspective EM, A&WMA's. *Mag Environ Manag* 10:26–34
- Gerharz LE, Klemm O, Broich AV, Pebesma E (2013) Spatio-temporal modelling of individual exposure to air pollution and its uncertainty. *Atmos Environ* 64:56–65. doi:10.1016/j.atmosenv.2012.09.069
- Gurram S, Stuart AL, Pinjari AR (2014) Impacts of travel activity and urbanicity on exposures to ambient oxides of nitrogen and on exposure disparities. *Air Qual Atmos Health* 1–18. doi:10.1007/s11869-014-0275-6
- Hannam K, McNamee R, De Vocht F, Baker P, Sibley C, Agius R (2013) A comparison of population air pollution exposure estimation techniques with personal exposure estimates in a pregnant cohort. *Environ Sci Processes Impacts* 15:1562–1572. doi:10.1039/c3em00112a
- Hystad P, Demers PA, Johnson KC, Carpiano RM, Brauer M (2013) Long-term residential exposure to air pollution and lung cancer risk. *Epidemiology* 24:762–772. doi:10.1097/EDE.0b013e3182949ae7
- Isaacs K, Glen G, McCurdy T, Smith L (2008) Modeling energy expenditure and oxygen consumption in human exposure models: accounting for fatigue and EPOC. *J Expo Sci Environ Epidemiol* 18: 289–298. doi:10.1038/sj.jes.7500594
- Jones NC, Thornton CA, Mark D, Harrison RM (2000) Indoor/outdoor relationships of particulate matter in domestic home with roadside, urban and rural locations. *Atmos Environ* 34:2603–2612
- Karner AA, Eisinger DS, Niemeier DA (2010) Near-roadway air quality: synthesizing the findings from real-world data. *Environ Sci Technol* 44:5334–5344. doi:10.1021/es100008x
- Kaufman JD et al (2012) Prospective study of particulate air pollution exposures, subclinical atherosclerosis, and clinical cardiovascular disease: the Multi-Ethnic Study of Atherosclerosis and Air Pollution (MESA Air). *Am J Epidemiol* 176:825–837. doi:10.1093/aje/kws169
- Kisku GC, Pradhan S, Khan AH, Bhargava SK (2013) Pollution in Lucknow City and its health implication on exposed vendors, drivers and traffic policemen. *Air Qual Atmos Health* 6:509–515. doi:10.1007/s11869-012-0190-7
- Kornartit C, Sokhi RS, Burton MA, Ravindra K (2010) Activity pattern and personal exposure to nitrogen dioxide in indoor and outdoor microenvironments. *Environ Int* 36:36–45. doi:10.1016/j.envint.2009.09.004
- Longley I, Somervell E, Gray S (2014) Roadside increments in PM10, NOx and NO2 concentrations observed over 2 months at a major highway in New Zealand. *Air Qual Atmos Health* 1–12. doi:10.1007/s11869-014-0305-4
- Ní Riain CM, Mark D, Davies M, Harrison RM, Byrne MA (2003) Averaging periods for indoor–outdoor ratios of pollution in naturally ventilated non-domestic buildings near a busy road. *Atmos Environ* 37:4121–4132. doi:10.1016/S1352-2310(03)00509-0
- NZTA (2013) State highway traffic data. New Zealand Transport Agency, Wellington
- Özkaynak H, Palma T, Touma JS, Thurman J (2008) Modeling population exposures to outdoor sources of hazardous air pollutants. *J Expo Sci Environ Epidemiol* 18:45–58

- Özkaynak H, Baxter LK, Dionisio KL, Burke J (2013) Air pollution exposure prediction approaches used in air pollution epidemiology studies. *J Expo Sci Environ Epidemiol* 23:566–572. doi:10.1038/jes.2013.15
- Pattinson W, Longley I, Kingham S (2014) Using mobile monitoring to visualise diurnal variation of traffic pollutants across two near-highway neighbourhoods. *Atmos Environ* 94:782–792. doi:10.1016/j.atmosenv.2014.06.007
- Patton AP, Collins C, Naumova EN, Zamore W, Brugge D, Durant JL (2014) An hourly regression model for ultrafine particles in a near-highway urban area. *Environ Sci Technol* 48:3272–3280. doi:10.1021/es404838k
- Perez L et al (2013) Chronic burden of near-roadway traffic pollution in 10 European cities (APHEKOM network). *Eur Respir J* 42:594–605. doi:10.1183/09031936.00031112
- Raw GJ, Coward SKD, Brown VM, Crump DR (2004) Exposure to air pollutants in English homes. *J Expo Anal Environ Epidemiol* 14: S85–S94
- Sarnat SE et al (2013) Application of alternative spatiotemporal metrics of ambient air pollution exposure in a time-series epidemiological study in Atlanta. *J Expo Sci Environ Epidemiol* 23:593–605. doi:10.1038/jes.2013.41
- Stroh E, Rittner R, Oudin A, Ardo J, Jakobsson K, Bjork J, Tinnerberg H (2012) Measured and modeled personal and environmental NO₂ exposure. *Popul Health Metrics* 10:10. doi:10.1186/1478-7954-10-10
- Tsigonia A, Lagoudi A, Chandrinou S, Linos A, Evlogias N, Alexopoulos EC (2010) Indoor air in beauty salons and occupational health exposure of cosmetologists to chemical substances. *Int J Environ Res Public Health* 7:314–324
- Vette A et al (2013) The Near-Road Exposures and Effects of Urban Air Pollutants Study (NEXUS): study design and methods. *Sci Total Environ* 448:38–47. doi:10.1016/j.scitotenv.2012.10.072
- Wang YJ, DenBleyker A, McDonald-Buller E, Allen D, Zhang KM (2011) Modeling the chemical evolution of nitrogen oxides near roadways. *Atmos Environ* 45:43–52. doi:10.1016/j.atmosenv.2010.09.050
- Xue J, McCurdy T, Burke J, Bhaduri B, Liu C, Nutaro J, Patterson L (2010) Analyses of school commuting data for exposure modeling purposes. *J Expo Sci Environ Epidemiol* 20:69–78. doi:10.1038/jes.2009.3
- You Y et al (2012) Measurement of air exchange rates in different indoor environments using continuous CO₂ sensors. *J Environ Sci* 24:657–664. doi:10.1016/S1001-0742(11)60812-7
- Zhu X, Fan ZT, Wu X, Jung KH, Ohman-Strickland P, Bonanno LJ, Lioy PJ (2011) Ambient concentrations and personal exposure to polycyclic aromatic hydrocarbons (PAH) in an urban community with mixed sources of air pollution. *J Expo Sci Environ Epidemiol* 21: 437–449. doi:10.1038/jes.2011.2
- Zidek JV, Shaddick G, White R, Meloche J, Chatfield C (2005) Using a probabilistic model (pCNEM) to estimate personal exposure to air pollution. *Environmetrics* 16:481–493. doi:10.1002/env.716
- Zou B, Wilson J, Zhan F, Zeng Y (2009) Air pollution exposure assessment methods utilized in epidemiological studies. *J Environ Monit* 11:475–490