



## Review

# A review of land-use regression models to assess spatial variation of outdoor air pollution

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## ABSTRACT

Studies on the health effects of long-term average exposure to outdoor air pollution have played an important role in recent health impact assessments. Exposure assessment for epidemiological studies of long-term exposure to ambient air pollution remains a difficult challenge because of substantial small-scale spatial variation. Current approaches for assessing intra-urban air pollution contrasts include the use of exposure indicator variables, interpolation methods, dispersion models and land-use regression (LUR) models. LUR models have been increasingly used in the past few years. This paper provides a critical review of the different components of LUR models.

We identified 25 land-use regression studies. Land-use regression combines monitoring of air pollution at typically 20–100 locations, spread over the study area, and development of stochastic models using predictor variables usually obtained through geographic information systems (GIS). Monitoring is usually temporally limited: one to four surveys of typically one or two weeks duration. Significant predictor variables include various traffic representations, population density, land use, physical geography (e.g. altitude) and climate.

Land-use regression methods have generally been applied successfully to model annual mean concentrations of NO<sub>2</sub>, NO<sub>x</sub>, PM<sub>2.5</sub>, the soot content of PM<sub>2.5</sub> and VOCs in different settings, including European and North-American cities. The performance of the method in urban areas is typically better or equivalent to geo-statistical methods, such as kriging, and dispersion models.

Further developments of the land-use regression method include more focus on developing models that can be transferred to other areas, inclusion of additional predictor variables such as wind direction or emission data and further exploration of focalsum methods. Models that include a spatial and a temporal component are of interest for (e.g. birth cohort) studies that need exposure variables on a finer temporal scale. There is a strong need for validation of LUR models with personal exposure monitoring.

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## 1. Introduction

A large number of epidemiological studies have shown that current day outdoor air pollution is associated with significant adverse effects on public health (Brunekreef and

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Holgate, 2002; Pope and Dockery, 2006). Pollutants of health concern at current day concentration levels in developed countries include particulate matter (PM), nitrogen dioxide (NO<sub>2</sub>) and ozone (Brunekreef and Holgate 2002). Time series studies have found that day-to-day changes in PM concentrations, in particular, are related to changes in hospital admissions and mortality (Katsouyanni et al., 2001; Samet et al., 2000). The relative risks in the time series studies are generally small: for example, in a large European study by Katsouyanni et al. (2001) mortality increased by 0.5% with an increase of 10 µg/m<sup>3</sup> of the 24-h average concentration of PM<sub>10</sub>. In 1993 a prospective cohort study in six US cities documented an association between long-term average exposure to outdoor air pollution and reduced survival, after careful control for other individual risk factors such as smoking (Dockery et al., 1993). Mortality rates in the most polluted city were 26% higher than in the least polluted city; the difference in annual average PM<sub>2.5</sub> concentration between these cities was 19 µg/m<sup>3</sup>. Several other studies have subsequently found associations between mortality from cardiovascular and respiratory diseases and long-term average exposure to air pollution (Pope and Dockery, 2006). In general, such long-term air pollution exposure studies have played an important role in recent health impact assessments and in the debate about new air quality guidelines for Europe (Kunzli et al., 2000).

Exposure assessment for epidemiological studies of long-term exposure to ambient air pollution remains a difficult challenge. The first cohort studies published in the mid-1990s have compared mortality rates between cities, with exposure characterized by the average concentration measured at a central site within each city (Dockery et al., 1993; Pope et al., 1995). In the past decade, various studies have documented significant variation of outdoor air pollution at a small scale within urban areas for important pollutants such as NO<sub>2</sub> and black smoke (e.g. Fischer et al., 2000; Kingham et al., 2000; Lebret et al., 2000; Monn, 2001; Jerrett et al., 2005; Zhu et al., 2002). In some settings the within-city spatial contrast may be as large as the between-city contrast. There is evidence from epidemiological studies that within-city contrasts of particulate matter air pollution are associated with larger contrasts than between-city (Miller et al., 2007). Epidemiological studies therefore need to take these contrasts into account. Monitoring alone will generally not be feasible, as the study population of epidemiological studies generally comprises several hundreds to thousands of subjects, living or working at different places. An additional complication for monitoring is that only long-term (i.e. annual) average concentrations are useful for the epidemiological study, so that multiple daily or weekly samples have to be collected.

Current approaches that have been developed to meet the challenge of assessing intra-urban air pollution contrasts have recently been reviewed (Briggs, 2005; Jerrett et al., 2005). Approaches include the use of exposure indicator variables (e.g. traffic intensity at the residential address or distance to a major road), interpolation methods (e.g. kriging, inverse distance weighing), conventional dispersion models and land-use regression models. Application of the land-use regression approach for air pollution

mapping was introduced in the SAVIAH (Small Area Variations In Air quality and Health) study (Briggs et al., 1997). Land-use regression combines monitoring of air pollution at a small number of locations and development of stochastic models using predictor variables usually obtained through geographic information systems (GIS). The model is then applied to a large number of unsampled locations in the study area. The technique was initially termed regression mapping (Briggs et al., 1997). Regression mapping is probably more descriptive of the methodology as the predictor variables are not only representative of land use. Other variables such as altitude and meteorology, for example, are often included in the models. As most researchers currently refer to the method as land use regression (LUR), however, we will also use this term. There are some earlier examples of the method in environmental science (Briggs et al., 1997). In 1985 interpolation of sulfate deposition data from the USA was supplemented with a drift term using geographical coordinates (Bilonick, 1985).

After the successful pioneering work in SAVIAH, LUR methods have been increasingly used in epidemiological studies in the past decade (Briggs, 2005). Developments in GIS have contributed to the popularity of LUR methods. Initially the approach was mainly adopted in Europe, but in the past few years several applications in North America have been published (e.g. Gilbert et al., 2005; Ross et al., 2006, 2007). While most studies have developed models that explain spatial air pollution contrasts satisfactorily, the predictive models differ substantially between the studies. Although this may be due to true differences between locations, we believe that differences in the application of the approach and selection of variables also play an important role.

The goal of this paper is therefore to review the various elements of the approach by discussing studies applying LUR methods. After listing the studies identified through a systematic review, we structure the review according to the main components of LUR: monitoring data, geographic predictors and model development and validation. We will compare the validity of the LUR models to alternative quantitative approaches especially dispersion modelling, and conclude with a discussion of limitations and new developments. A short review of LUR models has been published before (Ryan and LeMasters, 2007). The review identified six studies by a search through June 2006 and had a substantially narrower scope than the current manuscript.

### 1.1. Literature search

We performed a systematic literature search in Pubmed and Science Direct to trace studies using land-use regression approaches. The final search was conducted on January 15 2008. We used the search terms “land use regression”, “GIS air pollution”, “regression mapping” and “air pollution stochastic”. This was supplemented by papers included in the reference lists of the traced papers and papers that were already known to us based upon previous exposure assessment and epidemiological studies. We only included papers in the English, German and Dutch language.

## 2. Identified studies

We identified 25 land-use regression studies. Table 1 lists some key characteristics of the design of the studies we identified. Tables 2–5 outline the performance of, and predictor variables for, the final LUR models. Most applications have been limited to nitrogen dioxide (NO<sub>2</sub>), largely because of the ease of monitoring of this pollutant (Table 2). Fewer studies have developed models for NO or NO<sub>x</sub> (Table 3), particulate matter (PM<sub>2.5</sub>) or the elemental carbon content of particulate matter (Table 4) and VOCs including benzene and toluene (Table 5).

The SAVIAH study was the first to use land use regression to model small scale variations in air pollution (Briggs et al., 1997). The aim of the study was to generate individual-level indicators of long-term average exposure to ambient air pollution to assess the risks of respiratory disease of children. As the study population involved several thousand children, monitoring ambient air pollution at the home addresses was not feasible. Instead, in each of the three cities included in the study (Amsterdam, Huddersfield and Prague), a purpose-designed monitoring network of 80 monitoring sites was established to ensure a sufficiently dense network of monitoring stations. In none of the cities did a sufficiently dense routine monitoring network exist. At each site, the NO<sub>2</sub> concentration was measured for 14 days in each season with passive samplers (Lebrete et al., 2000). Measurements at all sites were performed simultaneously to avoid bias due to differences in weather conditions. The average concentration was then used to develop stochastic models. Variables potentially related to contrasts in air pollution, including measures of traffic, population density, land use and altitude were compiled in a GIS. The variables were then calculated for various buffers and linear regression was used to develop a model that explained the largest fraction of observed variability in annual average NO<sub>2</sub> concentration. The model was constrained by requiring that all regression coefficients have the a priori defined sign (e.g. positive for traffic and negative for altitude). The final prediction models explained between 61% and 72% of the observed variability in concentrations between sites (Briggs et al., 1997). Slightly different models were derived for each city due to differences between the cities, as well as differences in data availability (Table 2). Altitude, for example, was not a predictor in Amsterdam due to the flat terrain in this city; traffic intensity was a predictor in the Huddersfield and Prague models, but in Amsterdam was replaced by length of road by type, due to differences in data availability. Application of the models to validation sites not used in model development resulted in similar *R*<sup>2</sup> values, demonstrating the robustness of the models. In all three cities, LUR performed substantially better than spatial interpolation methods such as kriging, TIN-contouring and trend surface analysis (Briggs et al., 2000). In urban areas, spatial variability is characterized more by local sources such as major roads than as a smoothly varying concentration field, as assumed in spatial interpolation. In Huddersfield the regression model predicted measured concentrations at validation sites better than the CALINE-3 dispersion model (Briggs et al., 2000).

The method has subsequently been applied in a variety of settings, including Europe and more recently North America. Most studies were performed in a large urban area, sometimes including the surrounding smaller communities (Table 1). Three studies have applied the method to entire countries, specifically the Netherlands and the UK (Stedman et al., 1997; Hoek et al., 2001a,b; Beelen et al., 2007) while the APMOSPHERE project modelled concentrations on a 1 × 1 km scale for the EU-15 (Briggs et al., 2005).

Of the 25 identified studies, 12 studies mentioned that the final model was used in a specific identified epidemiological study (Aguilera et al., 2008; Beelen et al., 2007; Brauer et al., 2003; Briggs et al., 1997; Gilbert et al., 2005; Hoek et al., 2001a,b; Jerrett et al., 2007; Morgenstern et al., 2007; Ryan et al., 2007; Smith et al., 2006; Hochadel et al., 2006; Wheeler et al., 2008). Most other studies mentioned epidemiological studies as a rationale for modelling.

## 3. Monitoring data

Studies differ in the monitoring data that are used to develop land use regression models. Important aspects are the use of routine versus purpose-designed networks, monitored pollutant, the number and distribution of monitoring sites and temporal resolution.

### 3.1. Routine versus purpose-designed monitoring

A limited number of studies have made use of air pollution monitoring data from routine networks (Stedman et al., 1997; Hoek et al., 2001a,b; Beelen et al., 2007; Briggs et al., 2005; Moore et al., 2007; Ross et al., 2007; Briggs et al., *in press*). Most studies, however, have undertaken monitoring specifically for the purpose of model development as routine networks in most urban areas are not dense enough to enable meaningful modelling (Table 6) of small-scale variability of outdoor air pollution. A further advantage of purpose-designed monitoring is the control the investigators have over the type of sites (e.g. traffic, background) they wish to include in model development. Disadvantages of purpose-designed monitoring include the additional cost (discussed below) and the limited temporal coverage of the measurements. In the studies to date, most purpose-designed monitoring campaigns consisted of between one and four 7–14 days sampling campaigns, whereas routine monitoring is typically continuous, especially for the gaseous components. When routine monitoring data are used, however, careful attention must be paid to the site type as routine monitors are often designed to monitor compliance with regulatory standards rather than human exposures. As a result, routine networks are often focused at potential hotspots such as heavily trafficked street locations or industrial areas, and may consequently give biased estimates of pollution levels in areas where people live. Siting of monitors may differ substantially between countries: for example, in a paper from Canada routine network monitors were seen to be preferentially placed away from hotspots (Marshall et al., 2008).

In purpose-designed studies, NO<sub>2</sub>, NO, NO<sub>x</sub> and VOCs are generally measured with passive samplers, whereas PM is

**Table 1**  
Characterization of land-use regression studies

Reference	Study area	Pollutants	No. of monitoring sites	Selection of sites	Sampling period	Predictor variables collected
Briggs et al. (1997)	Amsterdam (NL)	NO <sub>2</sub>	80	Informal <sup>a</sup>	Four 2-week periods between June 1993 and June 1994	Traffic, land cover, altitude, sampling height
Stedman et al. (1997)	Huddersfield (UK) Prague (CZ) UK	NO <sub>2</sub> and NO <sub>x</sub>	80 80 37	All national monitoring network sites	Annual average 1994	Urban and suburban land cover, NO <sub>x</sub> emission from major road vehicle sources
Briggs et al. (2000)	Huddersfield (UK) Sheffield (UK) Northampton (UK)	NO <sub>2</sub>	20 28 35	Informal <sup>a</sup>	Twenty 2-week 1994–1995 Five 2-week 1997–1998 Six 2-week 1997–1998	Traffic, land cover, altitude, sampling height
Carr et al. (2002)	Munich, Germany	NO <sub>2</sub> , soot, VOC	34	Eighteen high traffic sites and 16 schools	Average December 1996–February 1998	Manually counted traffic intensity and percentage traffic jam
Brauer et al. (2003), Hoek et al. (2001b)	Netherlands Munich, Germany Stockholm, Sweden	PM <sub>2.5</sub> , soot, NO <sub>2</sub>	40 40 42	Informal <sup>a</sup>	Four 2-week periods between February 1999 and July 2000	Population and household density, traffic (traffic intensity, length of high traffic roads, distance to roads) and region
Gilbert et al. (2005)	Montreal, Canada	NO <sub>2</sub>	67	Population-weighted location-allocation model	One 2-week period May 2003	Distance and traffic counts nearest highway, area of open space and population density
Kanaroglou et al. (2005)	Toronto, Canada	NO <sub>2</sub>	100	Population-weighted location-allocation model	One 2-week period September 2002	Distance to the nearest expressway traffic in buffers; park, open, recreational, or water body land in buffer; household density
Gonzales et al. (2005)	El Paso, Texas, USA	NO <sub>2</sub>	20 Schools	Informal <sup>a</sup>	One 7-day period, February 11–18 1999	Distance to US–Mexico border, distance highway and altitude
Smith et al. (2006)	El Paso, Texas, USA	NO <sub>2</sub> , VOC	Twenty-two schools	Informal <sup>a</sup>	Two 7-day period, November–December 1999	Distance to US–Mexico border, distance highway and major roads, traffic intensity, altitude, population density, distance to petroleum facility
Briggs et al. (2005)	European Union (15 countries)	NO <sub>2</sub> , PM <sub>10</sub> and SO <sub>2</sub>	98–459	All background National Monitoring Network sites from AIRBASE	Annual average 2001	Altitude, distance to sea, climate, traffic, % non-residential urban land cover, % high density residential land cover, topography, % agriculture land cover
Ross et al. (2006)	San Diego County, California, US	NO <sub>2</sub>	39	Informal <sup>a</sup>	One 13–16 days period in October 2003	Traffic intensity, length of road, distance to Pacific coast
Hochadel et al. (2006)	North Rhine-Westphalia, Germany	NO <sub>2</sub> , PM <sub>2</sub> absorbance, PM <sub>2.5</sub>	40	Informal <sup>a</sup>	Four 2-week periods in March 2002–March 2003	Traffic intensity, number of buildings, distance to major roads
Sahsuvarglu et al. (2006)	Hamilton, Canada	NO <sub>2</sub>	107	Population-weighted location-allocation model	One 2-week period in October 2002	Land use, traffic, population density, physical geography, meteorology
Beelen et al. (2007), Hoek et al., 2001a	Netherlands	NO <sub>2</sub> , NO, and BS	16–36	All background National Monitoring Network sites	Average 1976–1996	Region, number of inhabitants in different buffer sizes, land use, traffic
Ross et al. (2007)	New York City (all 28 and 9 urbanized counties)	PM <sub>2.5</sub>	36–62	All routine Monitoring Network sites	3-Year averages 1999–2001 and average winter 2000	Traffic, population, land use and total county primary PM <sub>2.5</sub> emissions
Ryan et al. (2007)	Cincinnati, Ohio, US	Elemental carbon	24	Informal <sup>a</sup>	December 2001–December 2004 (total 609 samples)	Altitude, number of trucks, length of bus routes in buffers, land use

Author(s)	Location	Exposures	Sample size	Study design	Exposure assessment	Outcome
Morgenstern et al. (2007)	Munich, Germany	NO <sub>2</sub> , PM <sub>2.5</sub> filter absorbance, PM <sub>2.5</sub>	40	Informal <sup>a</sup>	Four 2-week periods between March 1999 and July 2000	Population and household density, traffic variables in buffers and land use
Rosenlund et al. (2008)	Rome, Italy	NO <sub>2</sub>	70	Schools in the SIDRIA study	Three 1-week periods June 1995–March 1996	Traffic, population, altitude, distance to sea, emission of pollutants
Moore et al. (2007)	Los Angeles, USA	PM <sub>2.5</sub>	23	All routine Monitoring Network sites	Annual average 2000	Land use, population, traffic, physical geography
Madsen et al. (2007)	Oslo, Norway	NO <sub>2</sub> , NO and NO <sub>x</sub>	80	Informal <sup>a</sup>	Two 1-week periods in February and March 2005	Land use, traffic, population density, altitude
Henderson et al. (2007)	Vancouver, CA	NO <sub>2</sub> , NO, PM <sub>2.5</sub> absorbance, PM <sub>2.5</sub>	25 (PM <sub>2.5</sub> ) 116 (NO and NO <sub>2</sub> )	Population-weighted location-allocation model	Two 2-week periods February/March and September 2003	Land use, traffic intensity, road length, population density
Terrett et al. (2007)	Toronto, Canada	NO <sub>2</sub>	95	Population-weighted location-allocation model	One 2-week period September 9–25, 2002	Land use, traffic, population density, physical geography, meteorology
Aguilera et al. (2008)	Sabadell, Spain	NO <sub>2</sub> , NO and BTEX	57	Informal <sup>a</sup>	Two to four 1-week periods between April 2005 and March 2006	Land use, traffic, population density, physical geography
Wheeler et al. (2008)	Windsor, Ontario, Canada	NO <sub>2</sub> , VOC	54	Informal <sup>a</sup>	Four 2-week periods in February, May, August and October 2004	Traffic, population density, dwelling density, land use, emission of pollutants
Briggs et al. (in press)	London, UK	PM <sub>10</sub>	52	All routine monitoring sites	Annual average 2001–2002	Land use, traffic, population density, meteorology

<sup>a</sup> Such that relevant site types and the study area were represented.

typically measured with active samplers. Passive samplers that have been used to monitor NO<sub>2</sub> include the Palmes tube (Briggs et al., 1997; Stedman et al., 1997; Brauer et al., 2003; Lewne et al., 2004; Ross et al., 2006) and the Ogawa badge (Gilbert et al., 2005; Kanaroglou et al., 2005; Sahsuvaroglu et al., 2006; Jerrett et al., 2007; Madsen et al., 2007; Henderson et al., 2007; Aguilera et al., 2008). Some studies that used the Ogawa badge also measured nitrogen oxides in the form of NO: this should represent primary emissions from combustion sources such as motorized traffic better than NO<sub>2</sub>, which has a significant secondary component (Madsen et al., 2007; Henderson et al., 2007; Aguilera et al., 2008).

Co-location of passive samplers at a few sites with continuous  $\text{NO}_x$  monitors has generally shown good agreement, but it remains important to include co-location in each new study. The two studies that involved specific PM monitoring used Harvard impactors which are low volume active samplers (Brauer et al., 2003; Hochadel et al., 2006). Elemental carbon was measured with a variety of approaches, including the conventional black smoke (BS) method (Brauer et al., 2003; Ryan et al., 2007) and thermal techniques (Carr et al., 2002; Ryan et al., 2007). Several studies have documented the very high correlation of these metrics (Cyrys et al., 2003).

Because of their more limited reliability, passive samplers have been deployed in duplicate at each site in some studies (Briggs et al., 1997; Ross et al., 2006; Jerrett et al., 2007). The low cost compared to active sampling allows duplicate sampling. The main advantage of duplicate sampling lies in detection of erroneous samples, and offering some information on measurement uncertainties, rather than increasing precision. Precision of a single measurement of  $\text{NO}_2$  determined from duplicate samples is typically 5–10%, which is acceptable.

Costs of passive sampling for NO<sub>x</sub> ( $n = 40$  sites, four surveys) are in the order of 10–12,000 Euro (Table 7). Costs of the same survey for active PM sampling are higher, up to 30,000 Euro, assuming that equipment is available (Table 7). Actual costs are dependent on the setting (e.g. ease of selecting monitoring locations) and salary rates. In addition, application of LUR involves costs of collecting and calculating the GIS variables or stochastic modelling, together with software or data licences. Nevertheless the overall costs of exposure assessment using LUR approaches are modest given typical budgets for large scale epidemiological studies.

### 3.2. Number and distribution of monitoring sites

There is no rigorous methodology to determine the required number of monitoring locations given a certain study objective and setting. Published studies have included between 20 and 100 sites, with the lower range representing those studies that modelled PM using routine monitoring data. Probably 40–80 sites is a reasonable number to choose for site-specific monitoring, but the size of the population and city should be taken into account to determine the actual number. Madsen et al. (2007) reported that models developed from a random selection of 40 sites in the Oslo urban area were indistinguishable from those developed using the full set of 80 monitoring sites. Oslo is a predominantly non-industrial



**Table 2**  
Performance of land-use regression models for NO<sub>2</sub>

Reference	Study area	Predictor variables in final model	R <sup>2</sup> of model	R <sup>2</sup> validation	RMSE validation (μg m <sup>-3</sup> )	Measured concentrations (μg m <sup>-3</sup> )
Briggs et al. (1997)	Amsterdam	Length major roads 50, 200, 350 m + Distance major road + built up land, 100 m	0.62	0.79	4.5 <sup>a</sup>	44 (12–73)
	Huddersfield	Traffic volume 300 m + land cover factor, 300 m + altitude + sampling height	0.61	0.82	3.7	30 (10–88)
	Prague	Traffic volume, 60 m + traffic volume 60–120 m + land cover factor 60 m + altitude	0.72	0.87	4.7	32 (6–83)
Briggs et al. (2000)	Huddersfield	Traffic density in two circular buffers (0–40 m and 40–300 m) weighted to produce a weighted traffic volume factor within a 300 m buffer + high density housing in a circular buffer (0–300 m) + altitude (log)	0.51	0.76	9.8 <sup>a</sup>	50 (SD 16)
	Sheffield		0.61	0.73	7.7	46 (SD 15)
	Northampton		0.60	0.58	5.5	27 (SD 9)
Stedman et al. (1997)	UK	Rural NO <sub>2</sub> + urban land cover 25 km <sup>2</sup> + urban land cover 100 + NO <sub>x</sub> emission major road vehicles 4 km <sup>2</sup>	0.97 <sup>b</sup>	0.36	–	–
Carr et al. (2002)	Munich, Germany	Traffic intensity 50 m + traffic intensity 50–300 m + traffic jam 50 m + traffic jam 50–300 m	0.77	NA	NA	50 (25–85)
Hoek et al. (2001b)	Netherlands	High traffic roads 250 m + address density 300 m + region + medium traffic roads 1000 m + address density 4000 m	0.85	–	4.7	29 (12–51)
		Traffic intensity 50 m + traffic intensity 50–250 m + address density 300 m + address density 300–5000 m	0.62	–	6.1	29 (16–51)
Gonzales et al. (2005)	Munich	Distance to US–Mexico border + distance highway + elevation	0.81	NR	NR	~40 (22–75)
Gilbert et al. (2005)	El Paso	Distance highway + traffic count nearest highway + length highways 100 m + length major roads 100 m + length minor roads 500 m + open space 100 m + population density 2000 m	0.55	0.52	–	23 ± 6 (10–42) <sup>c</sup>
	Montreal					
Smith et al. (2006)	El Paso	Elevation + traffic intensity 1000 m + population density + distance to border + distance petroleum facility	>0.90 <sup>e</sup>	–	~5.6	~44 (22–74) <sup>c</sup>
Briggs et al. (2005)	EU	Altitude + distance to sea + climate factor + traffic + % non-residential urban land cover + % high density residential land cover + topepx + % agriculture land cover	–	0.61	6.7	10 ± 6
Hochadel et al. (2006)	North Rhine-Westphalia	Heavy vehicle traffic 250–10,000 m + total traffic 250 m + maximum traffic 100 m + building density 1500 × 1500 m	0.90	–	2.7	26 (19–46) <sup>f</sup>
Ross et al. (2006)	San Diego County	Traffic density, 40–300 m + traffic density, 300–1000 m + road length, 40 m + distance Pacific coast	0.79	NR	NR	30 ± 9 (16–57) <sup>c</sup>
Sahsuvarglu et al. (2006)	Hamilton	Traffic density 300 m buffer + industrial land use, 200 m + open space land use, 500 m + <1500 m downwind highway 403 + within 50 m highways + distance Lake Ontario + downtown industrial core, 1000 m	0.76	NR	NR	29 ± 8 (16–56) <sup>c</sup>
Beelen et al. (2007)	Netherlands	Region + population 5000 m + urban land cover + city center + traffic intensity 100 m	0.84	NR	NR	–
Morgenstern et al. (2007)	Munich	Length state roads, 1000–2500 m + land cover factor, 100–250 m + land cover class + household density, 2500–5000 m + length rural roads, 250–500 m	0.51	–	9.51	29 (16–51)
Rosenlund et al. (2008)	Rome	Traffic zone + distance to busy roads + size census block + inverse population density + altitude	0.69	0.75	–	47 ± 10 (24–73)

Madsen et al. (2007)	Oslo	Altitude + length high traffic roads, 100 m + length medium traffic roads, 250 m + length small roads, 1000 m	0.77	0.70–0.80 <sup>d</sup>	–	37 (6–83)
Jerrett et al. (2007)	Toronto	Expressway, 200 m + major road, 50 m + industrial land use, 750 m + household density, 2000 m + X-coordinate + downwind within 1500 m expressway + traffic density, 500 m	0.69	NR	NR	64 ± 18 (34–122) <sup>e</sup>
Henderson et al. (2007)	Vancouver	Length expressway, 100 m + length expressway, 1000 m + length major roads, 200 m + population density, 2500 m + commercial area, 750 m + altitude + X-coordinate	0.56	0.69	2.8	32 ± 11
Aguilera et al. (2008)	Sabadell	Altitude + land cover factor, 500 m + road type (major, medium versus small roads)	0.75	0.68–0.74	1.6	40 ± 14 (19–76)
Wheeler et al. (2008)	Windsor	Distance to Ambassador bridge + length of expressways and highways, 50 m + length of major roads, 100 m	0.77	0.90	–	24 ± 6 (14–40)

Measured concentrations are mean ± standard deviation, with minimum and maximum in parentheses. RMSE, root mean squared error; NA, not available; NR, tabulated statistics not reported, but validation procedures performed resulting in typically small prediction errors.

<sup>a</sup> Values are standard errors of the estimate.

<sup>b</sup>  $R^2$  high because model includes rural NO<sub>2</sub> obtained through interpolation. Validation for background locations of the UK Diffusion tube survey, a different method.

<sup>c</sup> Assuming 1 ppb = 2 µg m<sup>-3</sup>.

<sup>d</sup> Three random subsets of 40 locations were drawn from the 80 sites (40 training and 40 validation samples).

<sup>e</sup> Artificially high as reported from Generalized Additive Model using 16 degrees of freedom with 22 observations.

<sup>f</sup> Median (min–max).

city of about 500,000 inhabitants located near the sea and with significant altitude differences. In Toronto, Canada, Jerrett et al. (2007) observed that models developed from random selections of 65 sites were very similar to a model developed for all 94 monitoring sites. Toronto is a city of 2.6 million people located on the shore of Lake Ontario and a study area of 633 km<sup>2</sup>. In London, LUR models derived for 75% of the 52 PM<sub>10</sub> sites were very similar (Briggs et al., in press). Whether these experiences are valid for other cities, in other types of environment, is unclear.

Fewer sites are most likely needed to transfer a model developed elsewhere to the study area of interest, as shown by Briggs and co-workers in the SAVIAH study. In this example, the model developed for Huddersfield was successfully applied in Huddersfield the following year and to three other UK cities, after recalibration with 10–11 sites in each city (Briggs et al., 2000). Local recalibration was necessary to take account of differences in meteorology, topography and vehicle fleet composition, and year-to-year changes in background concentrations (see further Section 5).

There are several ways in which to distribute monitoring sites over the study area once the total number of measurement sites has been fixed. Most studies have used informal methods to maximize the contrast in variables hypothesized to be potentially important predictors, by taking account of the distribution of locations to which the model will be applied. For example, in the TRAPCA study (Brauer et al., 2003) – designed to assess exposure for a birth cohort in three regions of the Netherlands – a total of 40 monitoring sites was available. It was decided to allocate 28 to urban and regional background locations and 12 to traffic locations. This decision was based upon the observation that, although only 5–10% of the population lived near major roads, those subjects were likely to experience substantially higher air pollution. It was thus decided to over-represent traffic sites in the monitoring campaign.

Kanaroglou et al. (2005) have developed a systematic methodology for selecting monitoring sites which uses the anticipated spatial variation in air pollution, as well as the distribution of addresses over the study area, to assign monitoring locations. The network density is increased in locations where concentration variability is higher and more people live. The method specifies a continuous demand (for monitoring) surface over the area. An algorithm from the general family of location-allocation problems is then used to select the optimal locations from a fixed number of monitoring sites. The demand surface incorporates an initial concentration surface, determined from, e.g. monitoring data in a wider area than the study area. The demand surface is then adapted by incorporating weights that reflect for example population density.

Another important issue is the micro-environment of monitoring sites, especially for traffic locations. If the purpose of the study is to assess exposure of people at the residential, school or work address, monitoring should take place near the façade of the homes rather than at the kerbside. Most prediction models are relatively crude (Tables 2–4) and unable to take account of small differences in distance, especially for urban roads (Brauer et al., 2003; Ross et al., 2007), though with high quality geographic data spatial resolutions of 20 m or so

**Table 3**Performance of land-use regression models for NO and NO<sub>x</sub>

Reference	Study area	Predictor variables in final model	R <sup>2</sup> of model	R <sup>2</sup> validation	RMSE model (validation)	Measured concentrations (µg m <sup>-3</sup> )
<b>NO</b>						
Beelen et al. (2007)	Netherlands	Region + population 5000 m + urban land cover + traffic intensity 100 m	0.44	NR	NR	–
Madsen et al. (2007)	Oslo	Altitude + length high traffic roads, 100 m + length medium traffic roads, 250 m + length small roads, 1000 m	0.66	0.66–0.70	–	22 (3–124)
Henderson et al. (2007)	Vancouver	Length expressway, 100 m + length expressway, 1000 m + length major roads, 200 m + population density, 2500 m + altitude + X + Y-coordinate	0.62	0.49	–	62 ± 43
<b>NO<sub>x</sub></b>						
Stedman et al. (1997)	UK	Rural NO <sub>x</sub> + urban land cover 25 km <sup>2</sup> + NO <sub>x</sub> emission major road vehicles 4 km <sup>2</sup>	0.96	NA	NA	–
Madsen et al. (2007)	Oslo	Altitude + length high traffic roads, 100 m + length medium traffic roads, 250 m + length small roads, 1000 m	0.73	0.68–0.78	–	–
Aguilera et al. (2008)	Sabadell	Altitude + land cover factor, 500 m + road type	0.77	0.67–0.75	2.4	60 ± 30 (27–161)

Measured concentrations are mean ± standard deviation, with minimum and maximum in parentheses. NA, not available; NR, tabulated statistics not reported, but validation procedures performed resulting in typically small prediction errors.

are possible (Briggs et al., 1997, 2000). This may be less of a problem for exposures related to major freeways because of the generally larger distances that are affected and the more open terrain. Studies of freeway exposures have included continuous functions of distance to the freeway in their models (Gilbert et al., 2005; Kanaroglou et al., 2005).

### 3.3. Temporal aspects

In the SAVIAH study, four monitoring periods of 14 days were conducted spread over the four seasons. Subsequent studies that undertook purpose-designed monitoring have made between one and four repeats of 7–14 days. Monitoring is thus temporally limited and the calculated average concentrations do not necessarily agree with the annual average due to the possibility that atypical weather conditions occur during the survey period. It should be noted, however, that the original SAVIAH monitoring scheme covered 56 days of the year, close to the number of days (60) covered in the once every sixth day PM<sub>10</sub> monitoring scheme in the USA, considered sufficient to establish an annual mean with good precision for regulatory purposes. More importantly, several studies have indicated that the spatial contrast between sampling sites is stable, provided that measurements are conducted simultaneously. In the SAVIAH study, the correlations between the four 14-day NO<sub>2</sub> sampling surveys ranged from 0.63 to 0.98 (Lebre et al., 2000). Correlations differed somewhat between cities: in Prague all correlations were above 0.92, whereas in Poznan the correlations were between 0.63 and 0.81. The authors also showed that between 63% and 84% of the total variability in NO<sub>2</sub> concentration was due to the between-site variability (Lebre et al., 2000). In Oslo, the correlation between two 1-week average concentrations was above 0.91 for NO, NO<sub>2</sub> and NO<sub>x</sub> (Madsen et al., 2007). In Hamilton, Canada the correlation between NO<sub>2</sub> concentrations measured at 30 sites in October 2002 and May 2004 was 0.76 (Sahsuaroglu et al., 2006). Strong support for the

stability of the spatial NO<sub>2</sub> pattern was provided by the observation that the predicted NO<sub>2</sub> concentrations in Amsterdam and Huddersfield correlated very well with measurements made the following year (Briggs et al., 1997). NO<sub>2</sub> pollution surfaces in Toronto, Canada based upon measurements in September 2002 and spring 2004, respectively, were essentially the same (Finkelstein and Jerrett, 2007).

Henderson et al. (2007) have suggested a methodology to select two 14-day monitoring periods. Using data from 15 routine monitoring sites for a 5-year period, they calculated all 14-day running means for all years and computed the average of the periods separated by 26 weeks. The average of two periods closest to the actual annual mean, and not explained by extreme values, was used to select the sampling periods. They observed the February 19–March 4 and August 24–September 2 periods resulted in average NO<sub>2</sub> that were within 15% of the actual annual mean for 70 out of 75 cases (Henderson et al., 2007). There is obviously no guarantee that, during the actual campaigns, this will apply, as weather conditions are unpredictable. Because of seasonal variations in air pollution concentrations, and the potential for individual sampling campaigns to coincide with sustained periods of abnormal weather (e.g. under blocking anticyclones), we therefore recommend a minimum of at least two and preferably four campaigns to be performed. In choosing periods for survey, it is also important to avoid events that might affect air pollution conditions, such as major festivals (e.g. 'Bonfire night' in the UK, which may last for at least a week) or religious holidays.

Studies that have measured PM at a large number of locations could not perform simultaneous measurements because of insufficient equipment. In these studies, therefore, corrections were applied using the measured concentrations at a continuous monitoring location (Hoek et al., 2002b). Application of this adjustment improved the precision of annual average PM<sub>2.5</sub> concentrations,



**Table 4**Performance of land-use regression models for fine particulate matter (PM<sub>2.5</sub> and soot)

Reference	Study area	Predictor variables	R <sup>2</sup> of model	R <sup>2</sup> validation	RMSE of model (validation)	Measured concentrations (µg m <sup>-3</sup> )
<b>PM<sub>2.5</sub> (µg m<sup>-3</sup>)</b>						
Brauer et al. (2003)	Netherlands	High traffic roads 250 m + address density 300 m + region	0.73	–	1.59	18 ± 3 (14–26) 14 ± 2 (11–20) 10 ± 2 (8–16)
	Munich	Traffic intensity 50 m + traffic intensity 50–250 m + address density 300 m	0.56	–	1.35	
	Stockholm County	Traffic intensity nearest road + population 1000–500 m	0.50	–	1.10	
Hochadel et al. (2006)	North Rhine-Westphalia	Heavy vehicle traffic 250–10,000 m + total traffic 250 m + distance major road + building density, 2500 × 2500 m	0.17	–	2.3	22 (14–25) <sup>d</sup>
Ross et al. (2007)	New York City, 28 counties	Traffic, 500 m + population, 1000 m + industrial land use, 300 m	0.64	–	1.1	14 ± 2 (10–20)
Moore et al. (2007)	Los Angeles, CA	Traffic density, 300 m + industrial land use, 5000 m + Government land area, 5000 m	0.69	NR	NR	18 ± 6 (9–28)
Morgenstern et al. (2007)	Munich	Land cover factor, 100–250 m + length rural roads, 100–250 m + distance motorway + population density, 500–1000 m	0.36	–	1.48	14 ± 2 (11–20)
Henderson et al. (2007)	Vancouver	Commercial area, 300 m + residential area, 750 m + industrial area, 300 m + altitude	0.52	0.09 <sup>e</sup>	1.5	4 ± 2 (1–9)
Briggs et al. (in press) <sup>f</sup>	London	Traffic intensity 20 m + traffic intensity 20–300 m + land cover 300 m	0.45–0.60	0.47	3.3	28 ± 5 (22–45)
<b>Soot</b>						
Carr et al. (2002) <sup>b</sup>	Munich, Germany	Traffic intensity 50 m + traffic intensity 50–300 m + traffic jam 50 m + traffic jam 50–300 m	0.80	NA	NA	10 (5–21)
Brauer et al. (2003) <sup>c</sup>	Netherlands	High traffic roads 250 m + address density 300 m + distance major road + region	0.81	–	0.3 × 10 <sup>-5</sup> m <sup>-1</sup>	1.6 ± 0.6 (0.8–3.2)
	Munich	Traffic intensity 50 m + traffic intensity 50–250 m + population density 300–5000 m	0.67	–	0.3 × 10 <sup>-5</sup> m <sup>-1</sup>	1.8 ± 0.4 (1.4–3.2)
	Stockholm County	Traffic intensity nearest road + population 1000–500 m	0.66	–	0.2 × 10 <sup>-5</sup> m <sup>-1</sup>	1.3 ± 0.4 (0.7–2.2)
Beelen et al. (2007) <sup>a</sup>	Netherlands	Region + population 1000 m + traffic intensity 100 m	0.59	NR	NR	
Hochadel et al. (2006) <sup>c</sup>	North Rhine-Westphalia	Heavy vehicle traffic 100–10000 m + total traffic 100 m + distance to highway	0.82	–	0.16 × 10 <sup>-5</sup> m <sup>-1</sup>	1.7 (0.9–2.5) <sup>d</sup>
Ryan et al. (2007) <sup>b</sup>	Cincinnati, Ohio, US	Altitude + truck density, 400 m + length bus routes, 100 m	0.75	NR	NR	0.5 ± 0.3 (0.2–1.0)
Morgenstern et al. (2007) <sup>c</sup>	Munich	Household density, 2500–5000 m + distance federal road + land cover factor, 100–250 m + length country roads, 1000 m	0.42	–	0.46 × 10 <sup>-5</sup> m <sup>-1</sup>	1.8 ± 0.4 (1.4–3.2)
Henderson et al. (2007) <sup>c</sup>	Vancouver	Length expressway, 1000 m + length major roads, 100 m + distance highway + open area, 500 m	0.39	–	0.4 × 10 <sup>-5</sup> m <sup>-1</sup>	0.8 ± 0.5 (0.2–2.4)

Measured concentrations are mean ± standard deviation, with minimum and maximum in parentheses. NA, not available; NR, tabulated statistics not reported, but validation procedures performed resulting in typically small prediction errors.

<sup>a</sup> Assessed as black smoke (µg m<sup>-3</sup>).

<sup>b</sup> Assessed as the elemental carbon content of filters (in the Carr study EC and absorbance but data reported as EC, µg m<sup>-3</sup>).

<sup>c</sup> Assessed as the absorbance of PM<sub>2.5</sub> filters using the reflectance measurement as used in the black smoke measurement.

<sup>d</sup> Median (min–max).

<sup>e</sup> Eight sites from routine monitoring network.

<sup>f</sup> PM<sub>10</sub> instead of PM<sub>2.5</sub>.

expressed as the standard error of the mean, from 2.0–3.5 µg m<sup>-3</sup> to 0.7–0.9 µg m<sup>-3</sup> (range for the three study areas: Munich, Stockholm and the Netherlands). It relies, however, on the assumptions that the air pollutant pattern across the study area is broadly stable over time (i.e. more polluted areas remain more polluted), and that the continuous monitoring site is representative of the temporal series. Sites used to adjust for temporal variations should

therefore be selected with care, and should not be subjected to local sources which might change over time (e.g. roads or major industrial emission sources).

#### 4. Predictor variables

Most studies have typically assessed a large set of potential predictor variables to model monitored concentrations.

**Table 5**

Performance of land-use regression models for VOC

Reference	Study area	Pollutants	Predictor variables	R <sup>2</sup> of model	R <sup>2</sup> validation	RMSE of model (validation)	Measured concentrations (µg m <sup>-3</sup> )
Carr et al. (2002)	Munich	Benzene	Traffic intensity 50 m + traffic intensity 50–300 m + traffic jam 50 m + traffic jam 50–300 m	0.80	NA	NA	6 (2–15)
		Ethyl-benzene		0.79			4 (1–5)
		Toluene		0.76			20 (6–44)
Smith et al. (2006)	El Paso	Benzene, ethyl-benzene, toluene, xylene	Altitude + traffic 1000 m + distance highway + population density + distance border + distance petroleum facility	>0.90 <sup>a</sup>	–	Relative RMSE 26–33%	5 (3–31)
Aguilera et al. (2008)	Sabadell	Benzene, ethyl-benzene, toluene, xylene	Altitude + land cover factor, 500 m + road type	0.74	0.71–0.75	2.2	17 ± 8 (4–34)
Wheeler et al. (2008)	Windsor	Benzene	Length of major roads, 100 m + length of expressways and primary highways, 50 m + VOC emission, 4000 m + VOC emission, 3000 m	0.73	0.78	–	0.9 (0.5–1.4)
		Toluene	Distance to Ambassador Bridge + length of major roads, 200 m + length of primary highways, 100 m + VOC emission, 1000 m	0.46	0.65	–	3 (1–6)

NA, not available; NR, tabulated statistics not reported, but validation procedures performed resulting in typically small prediction errors.

<sup>a</sup> Artificially high as reported from Generalized Additive Model using 16 degrees of freedom with 22 observations.

Frequently used predictor data include: traffic variables, population or address density, land use, altitude and topography, meteorology and location (Table 6). As an example, a study by Henderson et al. (2007) included 55 potential predictors and a study by Moore et al. (2007) examined 140 predictors. In the final models, typically only a small number of predictors are included. Definitions of the variables differ

substantially between studies (Tables 1–5). This is related to data availability, unique features of the study area (e.g. distance to a lake), and probably also a result of arbitrary decisions by the investigators.

Little attention has been given in the identified papers to the potential problems associated with geographic data sets. Problems may include accessibility, completeness and

**Table 6**

Overview of significant predictor variables in LUR studies

	Traffic <sup>a</sup>	Population <sup>b</sup>	Land use	Physical geography
Briggs et al. (1997)	Road length, distance, intensity		Composite	Altitude
Briggs et al. (2000)	Intensity	Housing		Altitude
Stedman et al. (1997)	Emission		Urban	
Hoek et al. (2001a,b)	Intensity, road length	Housing		Region country
Carr et al. (2002)	Intensity, congestion			
Brauer et al. (2003)	Intensity, road length	Housing		Region country
Gonzales et al. (2005)	Distance			Altitude, distance border
Gilbert et al. (2005)	Distance, intensity, road length	Population	Open space	
Smith et al. (2006)	Intensity	Population		Altitude, distance border
Briggs et al. (2005)	Road length	Housing	Multiple	Altitude, distance sea, climate, topex
Hochadel et al. (2006)	Intensity	Housing		
Ross et al. (2006)	Intensity, road length			Distance to sea
Sahsuvaroglu et al. (2006)	Intensity, distance		Industry, open space	Distance lake
Beelen et al. (2007)	Intensity	Population	Urban	Region country
Morgenstern et al. (2007)	Road length	Housing	Composite	
Rosenlund et al. (2008)	Distance	Population	City zone	Altitude
Madsen et al. (2007)	Road length			Altitude
Jerrett et al. (2007)	Road length, distance, intensity	Housing	Industry	Geographical coordinate
Henderson et al. (2007)	Road length,	Population	Commercial	Geographical coordinate, altitude
Aguilera et al. (2008)	Road length		Composite	Altitude
Moore et al. (2007)	Intensity		Industry, government	
Ross et al. (2007)	Intensity	Population	Industry	
Ryan et al. (2007)	Intensity, road length			Altitude
Briggs et al. (2008)	Intensity		Composite	
Wheeler et al. (2008)	Distance, road length			

<sup>a</sup> Distance to major roads/freeways, traffic intensity or length of road types without traffic intensity data.<sup>b</sup> Population or housing density.

**Table 7**

Approximate costs of land use regression monitoring campaigns with 40 sites and four weekly samples per site

Pollutants	No. samplers	Investment (Euro) <sup>a</sup>	Personnel (person days) <sup>b</sup>	Personnel (Euro)	Consumables (Euro) <sup>c</sup>
PM <sub>10</sub> + PM <sub>2.5</sub>	12	60,000	110	26,000	2000
NO <sub>x</sub>	40–80	3200–6400	30–40	7200–9600	1500–3000

<sup>a</sup> Unit prices of 5000 Euro for PM equipment consisting of pump and impactors used in the TRAPCA study (Hoek et al., 2002a,b; Brauer et al., 2003) and 80 Euro for the Ogawa badge. For PM monitoring the TRAPCA design was assumed with measurements at 10 sites simultaneous.

<sup>b</sup> PM: 64 days field work, 25 days of preparation (site selection, equipment) and 20 days sample analysis and data management. NO<sub>x</sub>: 16 days field work, 10 days preparation and 5 days analysis (preparation and analysis costs double if duplicates used at all sites). Tariff 30 Euro h<sup>-1</sup> for a technician.

<sup>c</sup> PM: 320 filters (PM<sub>10</sub> and PM<sub>2.5</sub>) at 5 Euro per filter plus QA/QC; NO<sub>x</sub>: 320 filters (NO<sub>2</sub> and NO<sub>x</sub>) at 3 Euro per piece. If duplicates are used for each site, consumable costs are double.

precision. Data may also not be available for the period of interest. This is especially an issue for retrospective exposure assessment. For a general discussion, see for example Briggs and Elliot (1995), Vine et al. (1997), Nuckols et al. (2004) and Briggs (2005). Traffic intensity data, especially those for municipal roads, are often problematic as they are not always accessible for the investigators, despite the fact that most traffic data have been obtained with public funds. In many cities, traffic counts are only available for a small number of streets, and mainly on major roads (Beelen et al., 2007; Madsen et al., 2007). Assumptions about the traffic intensity of other roads therefore must be made. Significant difficulties may also arise in attributing counts to the road network, because counts have to be extrapolated along and between road links. Traffic models can be used to assign traffic counts to other roads, and in some cities modelled data are available from transport and highways authorities. In the absence of traffic data, or to avoid the problems of acquiring them, several LUR studies have successfully explored the use of the length of specific road types without traffic intensity data (Brauer et al., 2003; Madsen et al., 2007; Henderson et al., 2007). In Vancouver, the  $R^2$  of the models based on traffic intensity did not differ from the models using only road length of highways and major roads for the evaluated pollutants (Henderson et al., 2007).

Predictor variables in LUR models are usually computed for circular zones around each monitoring site, using buffer functions in the GIS. The selection of buffer size is crucial in determining the performance of the model, and the spatial resolution of the estimates. Ideally, buffer sizes should be selected to take account of known dispersion patterns. Various monitoring studies have shown that the impact of a major road on concentrations of traffic-related air pollutants declines exponentially with distance to the road (Roorda-Knape et al., 1998). Beyond about 100 m from a major urban road, or 500 m from a major freeway, variability is limited. In inner-city areas, however, buildings may cause marked departures from this simple distance-decay pattern. In street canyons, for example, marked accumulation of air pollution may occur, especially against the windward side of buildings, with the result that concentrations may differ substantially from one side of the road to another. At the same time, NO<sub>2</sub> formation in street canyons may be limited by the availability of free oxygen, so that more of the pollution remains in NO form. There is also evidence to suggest that air pollution concentrations fall virtually to background levels behind a row of uninterrupted buildings (Bloemen et al., 1993). Especially in the compact European urban areas, much of the variation in

traffic-related air pollution is therefore extremely local. Use of buffer sizes of more than 100–200 m for traffic intensity may thus be misleading, for they would incorporate sources too far removed to have a significant effect.

The large spatial variability that occurs within tens of meters from major roads is potentially challenging given the geographic precision of monitoring sites, address and road data (Briggs et al., 1997; Hochadel et al., 2006). In a series of papers from Florida, it was reported that street geocoding resulted in substantial errors of the geographical position of homes and schools. This resulted in misclassification and bias of potential traffic exposures of children at home and at school (Zandbergen, 2007; Zandbergen and Green, 2007). In recent years, however, the spatial resolution of digital geographic data has improved considerably. In the Netherlands, for example, it is claimed that digital data sets of road lines are within 10 m of their true location for ca. 95% of road sections (Beelen et al., 2007). A sample of the Address Coordinates Netherlands showed that 93.5% of the addresses were located at the centroid of the correct building (Beelen et al., 2007). In a study in New York City, on the other hand, it was observed that the coordinates of older routine monitoring sites were not geographically precise (Ross et al., 2007). Uncertainties also occur in the traffic data, due to the limited representativeness of traffic counts and difficulties in extrapolating these across the network. In a Dutch study, it was found that direct observations of traffic by a technician at the monitoring sites improved the prediction models for soot and PM<sub>2.5</sub> over the GIS variables (Brauer et al., 2003). In studies with a moderate population size (several hundreds), therefore, it may be useful to include direct traffic observations at the home address. This is especially attractive if home visits have been planned to collect specific additional data for the epidemiological study of interest (e.g. collect house dust in a birth cohort study).

A further complication is the difficulty in obtaining data on height above ground for addresses. Geographical coordinates define the position using X- and Y-coordinates but do not necessarily have the height attached. In high-rise apartment buildings this may be an important issue, as several monitoring studies have suggested important differences in air pollution related to height (Vakeva et al., 1999; Janhall et al., 2003; Jo and Ky, 2002). In an elegant study in a major city in Korea, VOC concentrations were seen to be up to 70% higher outside low-floor (1st or 2nd) apartments compared to high-floor (10th–15th floor) apartments in the same building. Buildings were located within 30–100 m of a major road (Jo and Ky, 2002). Vertical

profiles were more pronounced during inversion and night-time hours. This suggests that applying LUR models in study areas where a large fraction of the population lives in high-rise apartment buildings may seriously misclassify exposure. Misclassification is especially an issue for buildings near major roads. There is very limited vertical gradient at urban background locations.

## 5. Model development and validation

Most studies use standard linear regression techniques to develop prediction models. Forward, backward or best-subsets automatic selection methods are often applied to develop a parsimonious model from a large set of predictor variables that maximizes the percentage explained variability ( $R^2$ ). Following the approach used in the SAVIAH study, a priori definition of a required sign of regression slopes for specific variables (e.g. positive for traffic intensity) is used by some investigators in order to increase the applicability of the model beyond the monitoring sites (Brauer et al., 2002; Henderson et al., 2007).

Four studies have used a structured approach in which different predictors were used for different spatial scales (Stedman et al., 1997; Hoek et al., 2001a; Briggs et al., 2005; Beelen et al., 2007). These were studies applying LUR models to larger geographical areas than most studies which model a large metropolitan area. In the Stedman study, a distinction was made between the rural and urban components. The rural scale was assessed by interpolating  $\text{NO}_2$  concentrations from rural monitoring sites. An urban component was added by regressing measured concentrations at urban sites against land use and emissions from motorized traffic. In the other three studies the spatial variation was assumed to comprise regional, urban and local components for which a different set of monitoring locations and predictor variables was used. A model was first developed for the regional and next for the urban and local scales. The advantage of this approach is that it incorporates more theoretical knowledge about processes governing spatial variation, hence increasing the likelihood that the developed model can be applied elsewhere. Furthermore, this approach reduces the likelihood of developing unrealistic models containing too many correlated predictor variables. Use of this multi-level or tiered approach is often limited, however, by the availability of enough rural monitoring sites, and it is in any event only applicable to studies covering large geographic areas in which regional scale variations are significant. Otherwise, it can generally be assumed that the constant in the LUR model represents the (invariant) regional background concentration.

Standard diagnostic tests for ordinary least squares regression should be applied, such as checks on the normality of residuals, heteroscedasticity and influential observations (e.g. Jerrett et al., 2007). As linear regression assumes independence of the residuals, most studies do check whether the residuals of the model exhibit spatial autocorrelation using a variety of techniques including kriging and Moran's  $I$  (Ross et al., 2007; Jerrett et al., 2007). Moran's  $I$  is a statistic between  $-1$  and  $+1$ , with  $0$  indicating no correlation of nearby sampling points. To calculate Moran's  $I$ , however, nearby needs to be defined – for example, as nearest neighbors (Ross et al., 2007). Most studies observed

that, while significant spatial autocorrelation is present in the measured concentrations, the residuals of land use regression models are independent (Sahsuvaroglu et al., 2006; Madsen et al., 2007; Jerrett et al., 2007; Ross et al., 2007), indicating that ordinary least squares regression can be used to obtain valid prediction models. In the APMO-SPHERE study covering the EU-15, significant autocorrelation remained in the residuals (Briggs et al., 2005). In that study, universal kriging was applied, which combines linear regression and ordinary kriging.

Some studies use the untransformed concentrations whereas other studies use the logarithm of the concentration (Gilbert et al., 2005; Henderson et al., 2007; Ryan et al., 2007; Moore et al., 2007; Madsen et al., 2007; Jerrett et al., 2007) in an attempt better to approximate a normal distribution of the residuals. When a log transformation is used, the interpretation of the model changes from an absolute contribution of variables in the model to a relative change, as illustrated by Gonzales et al. (2005).

Model validation is a crucial part of applying LUR methods. Virtually all land use regression studies have included some validation, though different approaches have been taken. One approach is leave-one-out cross-validation, in which a model is developed for  $n - 1$  sites and the predicted concentrations are compared with the actually measured concentrations at the left-out site. This procedure is repeated  $n$  times and the overall level of fit between the predicted and observed concentrations, across all sites, then computed as a measure of model performance. Usually the structure of the model remains constant for each estimate (Brauer et al., 2003; Hochadel et al., 2006). Another approach is to sub-divide the monitoring sites into a training data set for model development and a smaller group of sites for model validation (Briggs et al., 1997). This approach requires less intensive computer processing, but may be disadvantaged by the a priori division of sites (e.g. concentrations measured at the training and validation sites may differ). A combination of these approaches may provide a reasonable compromise. For example, a form of grouped jackknife analysis may be used, in which the monitoring sites could be divided into several ( $n$ ) equal groups, and the analysis repeated  $n$  times using a different group for validation such that all sites are used in model development and validation (Briggs et al., in press). Other approaches include comparison with databases that have not been used in model development, such as data from routine monitoring stations (e.g. Stedman et al., 1997; Henderson et al., 2007). Also, comparisons with measurements at the same sites in different time periods have been considered as validation. While it is very important to document temporal stability of the typically short monitoring data, the temporal comparison does not address the question of whether the model is able to predict spatial variability well.

### 5.1. Transferability

As mentioned above, little attention has been given to transferability of models to other locations. We believe that further exploration in this area would be beneficial for the wider application of the land use regression method. The

first systematic attempt was the study by Briggs et al. (2000) who successfully applied the SAVIAH model to other UK cities after calibration with a small number of monitoring sites. Jerrett et al. (2005) observed that application of the Amsterdam regression model reported by Briggs et al. (2000) did not explain spatial variation in the Hamilton area. The correlation of predicted NO<sub>2</sub> concentrations with government monitoring data was poor. This suggests that transfer of models will likely be limited by the availability of equivalent variables in other areas than the area where the model was developed, and models may not be transferred to areas that have a different structure in terms of land use. Jerrett et al. (2007) discuss differences in structure between European and North-American cities.

As land use regression models are empirical models – in contrast to dispersion models which are derived from physical principles – limitations in transferability may be inevitable to some extent. When possible, it is likely to be preferable to transfer models from nearby areas that have similar predictor variables, since this will not only increase the efficiency of applying LUR models, and thus reduce the cost of monitoring campaigns, but will also help to improve consistency between different studies. The potential of transferring models to other locations will be increased by the use of centralized (e.g. European) instead of local databases and somewhat less focus on maximizing the prediction  $R^2$ . Authors may report a best model (highest  $R^2$ ) with local predictors and a less predictive model that has more potential to be transferred.

## 6. Performance of models

Land-use regression methods have been applied to develop maps of NO<sub>2</sub>, NO<sub>x</sub>, PM<sub>2.5</sub>, the elemental carbon or soot content of PM<sub>2.5</sub> and VOCs. For NO<sub>2</sub>, the percentage explained variation from the prediction model is typically about 60–70%. This is often achieved with only a few predictors, usually including variables representing traffic load, population density, altitude and land use in various representations (e.g. industrial or urban). Differences in prediction  $R^2$  between studies may be related to the original variability in the measured concentrations, quality of the predictor variables, the modelling approach and the complexity of the city, for example, in terms of differences in topography and emission sources (Briggs, 2007). In five studies, the  $R^2$  from the prediction model and the cross-validation were very similar, documenting the robustness of the model (Briggs et al., 1997, 2000; Gilbert et al., 2005; Madsen et al., 2007; Henderson et al., 2007). In the Stedman study, the cross-validation  $R^2$  was much smaller than the  $R^2$  of the prediction model, possibly related to the use of a validation data set derived from sites using a different sampling methodology. Nevertheless, it illustrates the necessity of applying validation methods. Further support for the usefulness of LUR models is that the root mean squared error, in all studies that reported it, was low compared to the range in measured NO<sub>2</sub> concentrations.

The few studies that evaluated NO found similar  $R^2$  values to those for NO<sub>2</sub> in the same city (Tables 2 and 3). Henderson et al. (2007) demonstrated that the NO map developed for Vancouver showed more pronounced small-scale spatial

contrast than the NO<sub>2</sub> map, suggesting the importance of monitoring a primary pollutant.

Most studies were able to develop good predictive models for soot, and even for PM<sub>2.5</sub> that is characterized by a high regional background concentration with only limited impact of local sources (Table 4). The exception was the study in North-Rhine Westphalia where the  $R^2$  of the PM<sub>2.5</sub> model was only 17% compared to 82% for the absorbance of the PM<sub>2.5</sub> filters (Hochadel et al., 2006). Limited variability of the measured PM<sub>2.5</sub> concentrations in the small study area, further characterized by a lack of substantial altitude differences, is one likely explanation.

Three studies have suggested that VOCs can be modelled with LUR techniques, incorporating traffic variables and industrial sources. Monitoring of VOCs could be of interest in specific industrial settings, in assessing gas stations and in studies of specific health outcomes (e.g. leukemia). Because of the more demanding nature of monitoring compared to, for example, NO<sub>x</sub>, we see little merit in using VOCs as another indicator of traffic-related air pollution.

Several studies have compared LUR to commonly used methods such as geostatistics and dispersion modelling. In general LUR has been shown to outperform geostatistical methods. In SAVIAH, LUR predicted NO<sub>2</sub> concentrations in each of three European cities substantially better than geostatistical methods (Briggs et al., 2000). The percentage explained variability ( $R^2$ ) of measured NO<sub>2</sub> concentrations at validation sites was between 0.79 and 0.87 for LUR models, between 0.09 and 0.56 for TIN-contouring, 0.34 and 0.44 for kriging and between 0.27 and 0.48 for trend surface analysis in the three cities. In a study by Ross et al. (2007) in New York City, land use regression slightly outperformed kriging in predicting PM<sub>2.5</sub> concentrations at validation sites. The RMSE at prediction sites was 1.15 and 1.00  $\mu\text{g m}^{-3}$  for LUR in the '28-county' and 'more urbanized 9-county' models versus 1.30 and 1.47  $\mu\text{g m}^{-3}$  for kriging in these counties. The difference between the two studies is likely due to the much smoother spatial patterns for PM<sub>2.5</sub>, which has a strong regional background component. In London, the spatial variability of PM<sub>10</sub> across 52 monitoring sites was poorly predicted by kriging and nearest monitor site (validation  $R^2$  = 0.01 and 0.05), while an LUR model explained 47% of the measured variability (Briggs et al., in press).

Rather few comparisons have been made between LUR methods and dispersion modelling. Those that have been done suggest that LUR models perform as well as dispersion models in explaining spatial variation. In Huddersfield, UK, for example, land-use regression explained 82% of the variability of the NO<sub>2</sub> concentrations at validation sites whereas the CALINE-3 model explained 63% of the NO<sub>2</sub> variability (Briggs et al., 2000). In Munich, a stochastic model explained slightly more variability in NO<sub>2</sub> concentrations at the monitoring sites ( $R^2$  = 0.62) than a dispersion model ( $R^2$  = 0.46), although the modelled concentrations using the two approaches were highly correlated (Cyrys et al., 2005). In London, LUR models for PM<sub>10</sub> across 52 monitoring sites (assessed using the grouped jackknife approach) gave  $R^2$  of 0.47, compared with 0.28 for the ADMS-Urban dispersion model (Briggs et al., in press). In the Greater Vancouver area, predictions from LUR models



correlated better with concentrations from regulatory monitoring sites than the dispersion model CMAQ (NO:  $R = 0.75$  versus  $R = 0.46$  and NO<sub>2</sub>:  $R = 0.76$  and  $R = 0.71$ , respectively) (Marshall et al., 2008). The main difference between the LUR-model, the dispersion and the evaluated interpolation models was in the spatial scale that was described. LUR-models were better in describing hotspots whereas the other methods provided a smoother concentration surface (Marshall et al., 2008).

## 7. Limitations

While land use regression methods have, in many cases, been applied successfully to model spatial variation of ambient air pollution, there are several limitations of the method. First, LUR models have a limited ability to separate the impact of some priority pollutants. In the TRAPCA study, the correlation of modelled NO<sub>2</sub>, PM<sub>2.5</sub> and soot was above 0.95 in the three study areas (Munich, Stockholm and three regions in the Netherlands), so that the potentially independent health effects of these pollutants could not be evaluated (Brauer et al., 2002). Measured concentrations were also highly correlated ( $R^2$  of average NO<sub>2</sub> and PM<sub>2.5</sub> between 0.64 and 0.80 and between 0.76 and 0.86 for NO<sub>2</sub> and soot concentrations) (Lewne et al., 2004) but the relatively crude models increased the correlation of the modelled concentrations even further. In Munich, the correlation between NO<sub>2</sub> and PM<sub>2.5</sub> was 0.84 for measured concentrations and close to unity for modelled concentrations (Cyrus et al., 2005). More modest correlations were found in a small study area in Germany between PM<sub>2.5</sub> and NO<sub>2</sub> ( $r = 0.41$ ) and PM<sub>2.5</sub> and soot ( $r = 0.52$ ) (Hochadel et al., 2006). The correlation between soot and NO<sub>2</sub> was 0.93. Insofar as these correlations represent real associations between the different pollutants (rather than artifacts of the modelling procedures), the same problems will affect other methods of exposure assessment.

Second, LUR models may be unable to represent the extremely local variations in concentration (over distances of tens of meters) that may occur near sources such as major roads. This limitation, however, is mainly related to the precision of input data, and thus would also apply to dispersion models.

A third limitation of current LUR models is the often short temporal coverage of purpose-designed monitoring campaigns which does not allow the precise calculation of absolute concentrations that can be compared with air quality guidelines. Subject to the constraints mentioned earlier, this issue may be addressed by scaling the modelled concentrations using a continuous monitor in the study area. This is mainly an issue when maps are developed for regulatory purposes, much less so for application in epidemiological studies.

Fourth, dispersion models are superior when the interest is in a specific source-related component of the total concentration (e.g. traffic-derived particulates), since this can be separately modelled; in LUR models, in contrast, calibration against monitoring sites means that the model is usually designed to predict only the total concentration.

A further limitation is that, although land use regression models provide *individual* estimates of exposure at, for

example, the residential address, the estimate refers only to the ambient concentration. The predictor variables do not take account of factors (e.g. air exchange rate) related to infiltration of outdoor air in the home where people spend a large fraction of their time. Time activity patterns are also ignored: for example, the fraction of time actually spent at home is likely to be an important determinant. A more detailed discussion can be found in Briggs (2005), though this problem affects all methods of exposure assessment except personal monitoring or biomonitoring. To our knowledge, only one study has evaluated the contrast in personal exposure related to land use regression models (Nethery et al., 2007). In a group of 62 pregnant women, personal exposure of, especially, NO was moderately correlated with ambient NO assessed by land use regression. A few studies have further suggested that some of the traffic variables used in land use regression models are associated with small but significant contrasts in personal exposure of soot (Wichmann et al., 2005; Van Roosbroeck et al., 2006, 2007). Validation of the developed pollution maps with actual personal monitoring is therefore another important research need.

A final limitation worth noting is that some of the predictors used for developing air pollution exposures with LUR could introduce confounding when applied in epidemiological studies (Moore et al., 2007). LUR models including population density, for example, may be problematic as population density may also be associated with other adverse risk factors such as low socio-economic status or poor housing stock, which could influence the disease of interest (e.g. asthma prevalence). One solution to this potential problem is the inclusion of area-level confounders that are more closely related to the disease of interest (e.g. percentage of low-income families in a neighborhood) than the variable used in predicting air pollution (number of addresses in a 300 m buffer).

## 8. New developments

This section briefly outlines some innovations of the LUR methodology including expanding the scope of the predictor variables, new GIS approaches, and spatio-temporal models.

Rosenlund et al. (2008) evaluated the value of adding actual emission data to surrogate variables such as traffic intensity and population density to predict NO<sub>2</sub> concentrations in the city of Rome. No improvement of the land use regression model was obtained after adding emissions of PM, NO<sub>x</sub>, CO and benzene available at the census block level. In addition to assessing emissions from 164 census blocks, a continuous surface obtained through kriging was evaluated, but this did not improve the NO<sub>2</sub> prediction either. The limited spatial resolution of the emission data might have contributed to the lack of prediction. It is not clear whether these findings would apply in other cities. An early study by Stedman found that traffic emissions were highly predictive of UK-wide NO<sub>2</sub> concentrations, but the authors did not evaluate whether the same predictive power could have been obtained with traffic intensity only. In a study in New York City, primary PM<sub>2.5</sub> emissions available at the county level did not enter the final

prediction model for PM<sub>2.5</sub> (Ross et al., 2007). The study area consisted of 28 counties; hence data were available at a rather crude spatial scale.

Arain et al. (2007) assessed the use of wind fields to improve the prediction of air pollution in the Toronto–Hamilton urban airshed. Wind direction is an important variable that determines the impact of sources on receptor points, though it has rarely been incorporated into land-use regression models. Wind direction fields were constructed from 38 weather stations in the area and the constructed wind direction was found to be a significant predictor of NO<sub>2</sub> concentration. The  $R^2$  of the prediction increased from 0.65 without wind to 0.69 when wind direction was added to the model. It is not obvious whether the work required to construct the wind fields was worth the effort given this modest increase in prediction. As the authors appropriately point out, wind fields in urban areas should be very local in order to be useful.

Differences in dispersion conditions related to, for example, annual average wind speed may be important. In the simple CAR-2 model used in the Netherlands for modelling road-traffic emissions, the country is divided into different regions which are assigned different dispersion factors to reflect differences in wind speed related to distance to the sea (Eerens et al., 1993). In LUR models, this could be taken into account empirically by allowing the relationship between traffic intensity, or other source indicators, and air pollution concentrations to differ between different regions of the study area (interaction). This may be important when study areas are relatively large.

While modelled annual average concentrations are sufficient for most applications to epidemiological studies, birth cohort studies require more detailed temporal resolution. In these studies, it is common to express exposure as the average concentration per trimester of a specific pregnancy (Slama et al., 2007). The required exposure thus needs to contain a spatial and temporal component. To date this has not been systematically evaluated. One simple option is to develop LUR models using annual average concentrations as is commonly done and then use continuous routine monitoring data to adjust for the temporal component. This approach makes the assumption that the spatial pattern is constant in time. A more sophisticated approach was taken in a study on short-term air pollution variations (Maynard et al., 2007). In that study, a model was built that incorporated both time-varying and time-invariant factors in one model. Specifically, the black carbon (BC) concentration measured on a specific day at a specific location was modelled as a function of traffic within 100 m of the site (time-invariant), BC measured daily at a central continuous monitoring site, day of the week, weather and longitude and latitude. Non-parametric regression was used to allow for non-linear relationships between air pollution and predictor variables. The model performed substantially better than the central site measurement alone: cross-validation  $R^2$  was 0.36 compared to 0.09 for central site BC. Another approach is taken by a group of Canadian researchers who developed a source-area land use regression (SA-LUR) model, by combining concepts of a box-type dispersion model and land use regression to provide more

detailed temporal resolution (Su et al., 2008). Different scenarios with varying degrees of complexity of input data (wind direction, mixing height) were evaluated. The SA-LUR model was not superior to LUR in predicting long-term average concentrations, but did provide the flexibility for developing shorter-term exposures (Su et al., 2008). A key problem in the method was the ability to obtain sufficiently spatially detailed meteorological data.

Another innovation is the application of focalsum methods to construct weighted average prediction variables with a moving window approach. In this type of analysis, a window is 'moved' across a grid to derive a new value for the central cell, which is some function of the other cells covered by the window. In the context of air pollution modelling, this functionality can be used to smooth the spread of highly resolved data on pollution sources (e.g. emissions) to generate a map of concentrations. The fundamental principle behind the approach is that proximity to the source is one of the main determinants of pollutant concentrations. To date there exist few examples of moving window analysis for air pollution modelling. Collins (1998) was perhaps the first to explore the approach in a comparison of three GIS-based approaches in which traffic-related pollution was modelled in Huddersfield, UK. A distance-weighted kernel was used to model the near-source traffic-related component, which was subsequently added to a map of background concentrations derived from kriging. Validated against data from eight independent monitoring sites, the moving window approach ( $R^2 = 0.67$ ) performed better than kriging alone ( $R^2 = 0.44$ ), and was comparable to dispersion modelling ( $R^2 = 0.63$ ). The best model, however, was derived using land use regression ( $R^2 = 0.82$ ). Research by Loibl and Orthofer (2001) to produce a 250 m grid of NO<sub>2</sub> concentrations for Austria involved the use of weighted moving windows to apply existing dispersion profiles to point, line and area source emissions. Model validation indicated that 54% (72 sites) and 76% (101 sites) of the measurements at monitoring sites, respectively, were within  $\pm 15$  and  $\pm 25 \mu\text{g m}^{-3}$  of the model predictions. In general, however, their model tended to under-predict, especially at monitoring stations with high NO<sub>x</sub> contribution from traffic.

In more recent work, the moving window approach was further explored as an alternative method for modelling NO<sub>2</sub> at the 1 km level, across the EU-15 (Vienneau, 2006). The method estimated concentrations by calibrating the distance-weighted sum of emissions in concentric windows around each monitoring site to the monitored concentrations. The major advantage is that the models can be run within a raster GIS environment, which allows for rapid computation of large data sets. The models were developed using monitoring data from 714 background sites for 2001, and validated by comparing predictions with measured concentrations for a separate set of 228 reserved background sites ( $R^2 = 0.60$ ).

## 9. Conclusions

Land-use regression methods have generally been applied successfully to model annual mean concentrations of NO<sub>2</sub>, NO<sub>x</sub>, PM<sub>2.5</sub>, the soot content of PM<sub>2.5</sub> and VOCs. The method has been applied in different settings, including

European and North-American, non-industrial and industrial cities. The performance of the method in urban areas is typically better or equivalent to geo-statistical methods such as kriging and conventional dispersion models. Compared to dispersion models, the land use regression method requires less detailed input data at the expense of the need to obtain monitoring data for a sufficiently large number (40–80) of sites.

Land-use regression methods can benefit from a more systematic selection and description of monitoring locations and monitoring periods. More attention to the precision of geographic data is also important. A model strategy that incorporates greater knowledge of the factors related to spatial variation and focuses less on maximizing the percentage explained variability would probably result in models than can more readily be transferred to other areas. Where purpose-designed monitoring is included, the cost of monitoring could probably be reduced if models were transferable. Promising new developments include the use of additional predictor variables such as wind direction data or emission data and the use of the raster GIS environment – for example, to apply focalsum methods. Models that include both a spatial and a temporal component are also of interest for studies that need exposure variables on a more detailed scale, but it remains to be seen whether these LUR models can outperform dispersion models for shorter averaging periods. Finally, an area of importance for epidemiological research is the need for validation of LUR models with personal monitoring.

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## References

- Aguilera, I., Sunyer, J., Fernandez-Patier, R., Hoek, G., Aguirre-Alfaro, A., Meliefste, K., Bombai-Mingarro, M.T., Nieuwenhuijsen, M.J., Hoek, G., Brunekreef, B., group Is., et al., 2008. Estimation of outdoor NO<sub>x</sub>, NO<sub>2</sub> and BTEX exposure in a cohort of pregnant women using land use regression modeling. *Environ. Sci. Technol.* 42, 815–821.
- Araín, M.A., Blair, R., Finkelstein, N., Brook, J.R., Sahsuvarglu, T., Beckerman, B., Zhang, L., Jerrett, M., 2007. The use of wind fields in a land use regression model to predict air pollution concentrations for health exposure studies. *Atmos. Environ.* 41, 3453–3464.
- Beelen, R., Hoek, G., Fischer, P., van den Brandt, P.A., Brunekreef, B., 2007. Estimated long-term outdoor air pollution concentrations in a cohort study. *Atmos. Environ.* 41, 1343–1358.
- Bilonick, 1985. The space-time distribution of sulfate deposition in the Northeastern United States. *Atmos. Environ.* 19, 1829–1845.
- Bloemen, H.J.T., Balvers, T.T.M., van Scheindelen, H.J., Lebrecht, E., Oosterlee, A., Drijver, M., 1993. The Benzene Research in South of Kennemerland, The Netherlands. (Het benzeen onderzoek Zuid-Kennemerland). National Institute of Public Health and the Environment (RIVM) and Municipal Health Service Haarlem (GGD), Bilthoven.
- Brauer, M., Hoek, G., van Vliet, P., Meliefste, K., Fischer, P.H., Wijga, A., Koopman, L.P., Neijens, H.J., Gerritsen, J., Kerkhof, M., Heinrich, J., Bellander, T., Brunekreef, B., 2002. Air pollution from traffic and the development of respiratory infections and asthmatic and allergic symptoms in children. *Am. J. Respir. Crit. Care Med.* 166, 1092–1098.
- Brauer, M., Hoek, G., van Vliet, P., Meliefste, K., Fischer, P., Gehring, U., Heinrich, J., Cyrys, J., Bellander, T., Lewne, M., Brunekreef, B., 2003. Estimating long-term average particulate air pollution concentrations: application of traffic indicators and geographic information systems. *Epidemiology* 14, 228–239.
- Briggs, D., Elliot, P., 1995. The use of geographical information systems in studies on environment and health. *World Health Stat. Q.* 48, 85–94.
- Briggs, D., Collins, S., Elliot, P., Fischer, P., Kingham, S., Lebrecht, E., Pryl, K., Hv, Reeuwijk, Smallborne, K., Avd, Veen, 1997. Mapping urban air pollution using GIS: a regression-based approach. *Int. J. Geogr. Inf. Sci.* 11, 699–718.
- Briggs, D.J., de Hoogh, C., Gulliver, J., Wills, J., Elliott, P., Kingham, S., Smallbone, K., 2000. A regression-based method for mapping traffic-related air pollution: application and testing in four contrasting urban environments. *Sci. Total. Environ.* 253 (1–3), 151–167.
- Briggs, D., 2005. The role of GIS: coping with space (and time) in air pollution exposure assessment. *J. Toxicol. Environ. Health A* 68, 1243–1261.
- Briggs, D.J., Aaheim, A., Dore, C., Hoek, G., Petrakis, M., Shaddick, G., 2005. Air pollution modelling for support to policy on health and environmental risks in Europe. Final Report Section 6. Imperial College, London. EVK2-2002-00176. Available from: <http://www.apmosphere.org/>.
- Briggs, D.J., 2007. The role of GIS to evaluate traffic-related pollution. *Ed. Occup. Environ. Med.* 64, 1–2.
- Briggs, D., Hoogh, C.D. and Gulliver, J. Comparative assessment of GIS-based methods and metrics for modeling exposure to air pollution. *J. Toxicol. Environ. Health.*, in press.
- Brunekreef, B., Holgate, S.T., 2002. Air pollution and health. *Lancet* 360, 1233–1242.
- Carr, D., von Ehrenstein, O., Weiland, S., Wagner, C., Wellie, O., Nicolai, T., von Mutius, E., 2002. Modeling annual benzene, toluene, NO<sub>2</sub>, and soot concentrations on the basis of road traffic characteristics. *Environ. Res.* 90, 111–118.
- Collins, S., 1998. A GIS approach to modelling traffic related air pollution. Ph.D. thesis, The University of Huddersfield.
- Cyrys, J., Heinrich, J., Hoek, G., Meliefste, K., Lewne, M., Gehring, U., Bellander, T., Fischer, P., van Vliet, P., Brauer, M., Wichmann, H.E., Brunekreef, B., 2003. Comparison between different traffic-related particle indicators: elemental carbon (EC), PM<sub>2.5</sub> mass, and absorbance. *J. Expo. Anal. Environ. Epidemiol.* 13, 134–143.
- Cyrys, J., Hochadel, M., Gehring, U., Hoek, G., Diegmann, V., Brunekreef, B., Heinrich, J., 2005. GIS-based estimation of exposure to particulate matter and NO<sub>2</sub> in an urban area: stochastic versus dispersion modeling. *Environ. Health Perspect.* 113, 987–992.
- Dockery, D.W., Pope III, C.A., Xu, X., Spengler, J.D., Ware, J.H., Fay, M.E., Ferris Jr., B.G., Speizer, F.E., 1993. An association between air pollution and mortality in six U.S. cities. *N. Engl. J. Med.* 329, 1753–1759.
- Eerens, H., Sliggers, C., Hout, K.V.D., 1993. The CAR model: the Dutch method to determine city air quality. *Atmos. Environ.* 27B, 389–399.
- Finkelstein, M.M., Jerrett, M., 2007. A study of the relationships between Parkinson's disease and markers of traffic-derived and environmental manganese air pollution in two Canadian cities. *Environ. Res.* 104, 420–432.
- Fischer, P., Hoek, G., Hv, Reeuwijk, Briggs, D.J., Lebrecht, E., Wijnen, J.V., Kingham, S., Elliot, P., 2000. Traffic-related differences in outdoor and indoor concentrations of particles and volatile organic compounds in Amsterdam. *Atmos. Environ.* 34, 3713–3722.
- Gilbert, N.L., Goldberg, M.S., Beckerman, B., Brook, J.R., Jerrett, M., 2005. Assessing spatial variability of ambient nitrogen dioxide in Montreal, Canada, with a land-use regression model. *J. Air Waste Manage. Assoc.* 55, 1059–1063.
- Gonzales, M., Qualls, C., Hudgens, E.L., Neas, L.N., 2005. Characterization of a spatial gradient of nitrogen dioxide across a United States – Mexico border city during winter. *Sci. Total Environ.* 337, 163–173.
- Henderson, S., Beckerman, B., Jerrett, M., Brauer, M., 2007. Application of land use regression to estimate long-term concentrations of traffic-related nitrogen oxides and fine particulate matter. *Environ. Sci. Technol.* 41, 2422–2428.
- Hochadel, M., Heinrich, J., Gehring, U., Morgenstern, V., Kuhlbusch, T., Link, E., Wichmann, H.E., Kramer, U., 2006. Predicting long-term average concentrations of traffic-related air pollutants using GIS-based information. *Atmos. Environ.* 40, 542–553.
- Hoek, G., Fischer, P., van den Brandt, P.A., Goldbohm, S., Brunekreef, B., 2001a. Estimation of long-term average exposure to outdoor air pollution for a cohort study on mortality. *J. Expo. Anal. Environ. Epidemiol.* 11, 459–469.
- Hoek, G., Meliefste, K., Brauer, M., Vliet, P.V., Brunekreef, B., Fischer, P., Lebrecht, E., Cyrys, J., Gehring, U., Heinrich, J., Wichmann, H.E., Lewne, M., Bellander, T., Pershagen, G., 2001b. Risk assessment of exposure to traffic-related air pollution for the development of inhalant allergy, asthma and other chronic respiratory conditions in children (TRAPCA). Final Report, IRAS. University Utrecht, Utrecht.

- Hoek, G., Brunekreef, B., Goldbohm, S., Fischer, P., van den Brandt, P.A., 2002a. Association between mortality and indicators of traffic-related air pollution in the Netherlands: a cohort study. *Lancet* 360, 1203–1209.
- Hoek, G., Meliefste, K., Cyrys, J., Lewne, M., Bellander, T., Brauer, M., Fischer, P., Gehring, U., Heinrich, J., van Vliet, P., Brunekreef, B., 2002b. Spatial variability of fine particles concentrations in three European areas. *Atmos. Environ.* 36, 4077–4088.
- Janhall, S., Molnar, P., Hallquist, M., 2003. Vertical distribution of air pollutants at the Gustavii Cathedral in Goteborg, Sweden. *Atmos. Environ.* 37, 209–217.
- Jerrett, M., Arain, A., Kanaroglou, P., Beckerman, B., Potoglou, D., Sahsuvaroglu, T., Morrison, J., Giovis, C., 2005. A review and evaluation of intraurban air pollution exposure models. *J. Expo. Anal. Environ. Epidemiol.* 15, 185–204.
- Jerrett, M., Arain, M.A., Kanaroglou, P., Beckerman, B., Crouse, D., Gilbert, D., Brook, J.R., Finkelstein, N., Finkelstein, M.M., 2007. Modeling the intraurban variability of ambient traffic pollution in Toronto, Canada. *J. Toxicol. Environ. Health Part A* 70, 200–212.
- Jo, W.K., Ky, K., 2002. Vertical variability of volatile organic compound (VOC) levels in ambient air of high-rise apartment buildings with and without occurrence of surface inversion. *Atmos. Environ.* 36, 5645–5652.
- Kanaroglou, P.S., Jerrett, M., Morrison, J., Beckerman, B., Altaf Arain, M., Gilbert, N.L., Brook, J.R., 2005. Establishing an air pollution monitoring network for intra-urban population exposure assessment: a location-allocation approach. *Atmos. Environ.* 39, 2399–2409.
- Katsouyanni, K., Touloumi, G., Samoli, E., Gryparis, A., Le Tertre, A., Monopoli, Y., Rossi, G., Zmirou, D., Balaster, F., Boumghar, A., Anderson, H.R., Wojtyniak, B., Paldy, A., Braunstein, R., Pekkanen, J., Schindler, C., Schwartz, J., 2001. Confounding and effect modification in the short-term effects of ambient particles on total mortality: results from 29 European cities within the APHEA2 project. *Epidemiology* 12, 521–531.
- Kingham, S., Briggs, D., Elliot, P., Fischer, P., Lebret, E., 2000. Spatial variations in the concentrations of traffic-related pollutants in indoor and outdoor air in Huddersfield, England. *Atmos. Environ.* 34, 905–916.
- Kunzli, N., Kaiser, R., Medina, S., Studnicka, M., Chanel, O., Filliger, P., Herry, M., Horak Jr., F., Puybonnieux-Texier, V., Quenel, P., Schneider, J., Seethaler, R., Vergnaud, J.C., Sommer, H., 2000. Public-health impact of outdoor and traffic-related air pollution: a European assessment. *Lancet* 356, 795–801.
- Lebret, E., Briggs, D., Reeuwijk, H.V., Fischer, P., Smallbone, K., Harssema, H., Kriz, B., Gorynski, P., Elliot, P., 2000. Small area variations in ambient NO<sub>2</sub> concentrations in four European areas. *Atmos. Environ.* 34, 177–185.
- Lewne, M., Cyrys, J., Meliefste, K., Hoek, G., Brauer, M., Fischer, P., Gehring, U., Heinrich, J., Brunekreef, B., Bellander, T., 2004. Spatial variation in nitrogen dioxide in three European areas. *Sci. Total Environ.* 332, 217–230.
- Loibl, W., Orthofer, R., 2001. From national emission totals to regional ambient air quality information for Austria. *Adv. Environ. Res.* 5, 395–404.
- Madsen, C., Lodrup-Carlsen, K.C., Hoek, G., Oftedal, B., Nafstad, P., Meliefste, K., Jacobsen, R., Nystad, W., Carlsen, K.H., Brunekreef, B., 2007. Modeling the intra-urban variability of outdoor traffic pollution in Oslo, Norway – a GA2LEN project. *Atmos. Environ.* 41, 7500–7511.
- Marshall, J.D., Nethery, E., Brauer, M., 2008. Within-urban variability in ambient air pollution: comparison of estimation methods. *Atmos. Environ.* 42, 1359–1369.
- Maynard, D., Coull, B.A., Alexandros, G., Joel, S., 2007. Mortality risk associated with short-term exposure to traffic particles and sulfates. *Environ. Health Perspect.* 115, 751–755.
- Miller, K.A., Siscovick, D.S., Sheppard, L., Shepherd, K., Sullivan, J.H., Anderson, G.L., Kaufman, J.D., 2007. Long-term exposure to air pollution and incidence of cardiovascular events in women. *N. Engl. J. Med.* 356, 447–458.
- Monn, C., 2001. Exposure assessment of air pollutants: a review on spatial heterogeneity and indoor/outdoor/personal exposure to suspended particulate matter, nitrogen dioxide and ozone. *Atmos. Environ.* 35, 1–32.
- Moore, D.K., Jerrett, M., Mack, W.J., Kunzli, N., 2007. A land use regression model for predicting ambient fine particulate matter across Los Angeles, CA. *J. Environ. Monitor.* 9, 246–252.
- Morgenstern, V., Zutavern, A., Cyrys, J., Brockow, I., Gehring, U., Koletzko, S., Bauer, C.P., Reinhardt, D., Wichmann, H.E., Heinrich, J., 2007. Respiratory health and individual estimated exposure to traffic-related air pollutants in a cohort of young children. *Occup. Environ. Med.* 64, 8–16.
- Nethery, E., Leckie, S.E., Teschke, K., Brauer, M., 2007. From measures to models: an evaluation of air pollution exposure assessment for epidemiologic studies of pregnant women. *Occup. Environ. Med.* doi:10.1136/oem.2007.035337.
- Nuckols, J.R., Ward, M.H., Jarup, L., 2004. Using geographic information systems for exposure assessment in environmental epidemiology studies. *Environ. Health Perspect.* 112, 1007–1015.
- Pope III, C.A., Thun, M.J., Namboodiri, M.M., Dockery, D.W., Evans, J.S., Speizer, F.E., Heath Jr., C.W., 1995. Particulate air pollution as a predictor of mortality in a prospective study of U.S. adults. *Am. J. Respir. Crit. Care Med.* 151, 669–674.
- Pope 3rd, C.A., Dockery, D.W., 2006. Health effects of fine particulate air pollution: lines that connect. *J. Air Waste Manage. Assoc.* 56, 709–742.
- Roorda-Knappe, M.C., Janssen, N.A.H., de Hartog, J., van Vliet, P.H.N., Harssema, H., Brunekreef, B., 1998. Air pollution from traffic in city districts near major motorways. *Atmos. Environ.* 32, 1921–1930.
- Rosenlund, M., Forastiere, F., Stafoggia, M., Porta, D., Perucci, M., Ranzi, A., Nussio, F., Perucci, C.A., 2008. Comparison of regression models with land-use and emissions data to predict the spatial distribution of traffic-related air pollution in Rome. *J. Expo. Sci. Environ. Epidemiol.* 18, 192–199.
- Ross, Z., English, P.B., Scalf, R., Gunier, R., Smorodinsky, S., Wall, S., Jerrett, M., 2006. Nitrogen dioxide prediction in Southern California using land use regression modeling: potential for environmental health analyses. *J. Expo. Sci. Environ. Epidemiol.* 16, 106–114.
- Ross, Z., Jerrett, M., Ito, K., Tempalski, B., Thurston, G.D., 2007. A land use regression for predicting fine particulate matter concentrations in the New York City region. *Atmos. Environ.* 41, 2255–2269.
- Ryan, P.H., LeMasters, G.K., 2007. A review of land-use regression models for characterizing intraurban air pollution exposure. *Inhal. Toxicol.* 19 (Suppl. 1), 127–133.
- Ryan, P.H., LeMasters, G.K., Biswas, P., Levin, L., Hu, S., Lindsey, M., Bernstein, D.I., Lockey, J.E., Villareal, M., Khurana Hershey, G.K., Grinshpun, S.A., 2007. A comparison of proximity and land use regression traffic exposure models and wheezing in infants. *Environ. Health Perspect.* 115, 278–284.
- Sahsuvaroglu, T., Arain, A., Kanaroglou, P., Finkelstein, N., Newbold, B., Jerrett, M., Beckerman, B., Brook, J., Finkelstein, M., Gilbert, D., 2006. A land use regression model for predicting ambient concentrations of nitrogen dioxide in Hamilton, Ontario, Canada. *J. Air Waste Manage. Assoc.* 56, 1059–1069.
- Samet, J.M., Dominici, F., Currier, F.C., Coursac, I., Zeger, S.L., 2000. Fine particulate air pollution and mortality in 20 U.S. cities, 1987–1994. *N. Engl. J. Med.* 343, 1742–1749.
- Slama, R., Morgenstern, V., Cyrys, J., Zutavern, A., Herbarth, O., Wichmann, H.E., Heinrich, J., 2007. Traffic-related atmospheric pollutants levels during pregnancy and offspring's term birth weight: a study relying on a land-use regression exposure model. *Environ. Health Perspect.* 115, 1283–1292.
- Smith, L., Mukerjee, S., Gonzales, M., Stallings, C., Neas, L., Norris, G., H O, 2006. Use of GIS and ancillary variables to predict volatile organic compound and nitrogen dioxide levels at unmonitored locations. *Atmos. Environ.* 40, 3773–3787.
- Stedman, J., Vincent, K., Campbell, G., Goodwin, J., Downing, C., 1997. New high resolution maps of estimated background ambient NO<sub>x</sub> and NO<sub>2</sub> concentrations in the U.K. *Atmos. Environ.* 31, 3591–3602.
- Su, J.G., Brauer, M., Ainslie, B., Steyn, D., Larsson, T., Buzzelli, M., 2008. An innovative land use regression model incorporating meteorology for exposure analysis. *Sci. Total Environ.* doi:10.1016/j.scitotenv.2007.10.032.
- Vakeva, M., Hameri, K., Kulmala, M., Lahdes, R., Ruuskanen, J., Laitinen, T., 1999. Street level versus rooftop concentrations of submicron aerosol particles and gaseous pollutants in an urban street canyon. *Atmos. Environ.* 33, 1385–1397.
- Van Roosbroeck, S., Wichmann, J., Janssen, N.A., Hoek, G., van Wijnen, J.H., Lebret, E., Brunekreef, B., 2006. Long-term personal exposure to traffic-related air pollution among school children, a validation study. *Sci. Total Environ.* 368 (2–3), 565–573.
- Van Roosbroeck, S., Jacobs, J., Janssen, N., Oldenwening, M., Hoek, G., Brunekreef, B., 2007. Long-term personal exposure to PM<sub>2.5</sub>, soot and NO<sub>x</sub> in children attending schools located near busy roads, a validation study. *Atmos. Environ.* 41, 3381–3394.
- Vienneau, D., 2006. Spatial Modelling of Air Pollution for Exposure Assessment. Imperial College, London.
- Vine, M.F., Degnan, D., Hanchette, C., 1997. Geographic information systems: their use in environmental epidemiologic research. *Environ. Health Perspect.* 105, 598–605.
- Wheeler, A.J., Smith-Doiron, M., Xu, X., Gilbert, N.L., Brook, J.R., 2008. Intra-urban variability of air pollution in Windsor, Ontario – measurement and modeling for human exposure assessment. *Environ. Res.* 106, 7–16.

- Wichmann, J., Janssen, N., van der Zee, S., Brunekreef, B., 2005. Traffic-related differences in indoor and personal absorption coefficient measurements in Amsterdam, the Netherlands. *Atmos. Environ.* 39, 7384–7392.
- Zandbergen, P.A., 2007. Influence of geo-coding quality on environmental exposure assessment of children living near high traffic roads. *BMC Public Health* 7.
- Zandbergen, P.A., Green, J.W., 2007. Error and bias in determining exposure potential of children at school locations using proximity-based GIS techniques. *Environ. Health Perspect.* 115, 1363–1370.
- Zhu, Y., Hinds, W., Kim, S., Shen, S., Sioutas, C., 2002. Study of ultrafine particles near a major highway with heavy-duty diesel traffic. *Atmos. Environ.* 36, 4323–4335.