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# A review and evaluation of intraurban air pollution exposure models

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The development of models to assess air pollution exposures *within* cities for assignment to subjects in health studies has been identified as a priority area for future research. This paper reviews models for assessing intraurban exposure under six classes, including: (i) proximity-based assessments, (ii) statistical interpolation, (iii) land use regression models, (iv) line dispersion models, (v) integrated emission-meteorological models, and (vi) hybrid models combining personal or household exposure monitoring with one of the preceding methods. We enrich this review of the modelling procedures and results with applied examples from Hamilton, Canada. In addition, we qualitatively evaluate the models based on key criteria important to health effects assessment research. Hybrid models appear well suited to overcoming the problem of achieving population representative samples while understanding the role of exposure variation at the individual level. Remote sensing and activity–space analysis will complement refinements in pre-existing methods, and with expected advances, the field of exposure assessment may help to reduce scientific uncertainties that now impede policy intervention aimed at protecting public health.
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## Introduction

The development of models to assess air pollution exposures *within* cities for assignment to subjects in health studies has been identified as a priority area for future research (Brunekreef and Holgate, 2002; Brauer et al., 2003). While surrogate measures, such as distance to roads, have been related to large health effects (Hoek et al., 2002), these may misclassify exposure because they are not directly estimated from monitored data. Potential alternatives to surrogate measures arise from geographic and dispersion exposure methods. These methods utilize geographic information systems (GIS) to combine available geographic data with short-term monitoring information to develop exposure models capable of identifying small-area variations in pollution. Results from these models can then be overlaid on geo-referenced health data to assign exposure to individuals at their place of residence, work, or some combination of both.

Interest in assessing exposure to ambient air pollution at the intraurban scale (i.e., within-city scale) has increased for a variety of reasons. First, the contribution of traffic pollution has grown, and most studies agree that the demand for transportation will exceed improvements to emission reduction technologies (Faiz, 1993; Delucchi, 2000). Regardless of regulatory interventions, higher exposure to traffic pollution with distinct intraurban gradients may be seen around major roads and highways (Gilbert et al., 2002). Recent exposure studies have shown that for some pollutants associated with traffic, such as nitrogen dioxide ($NO_2$) and ultrafine particles, variation within cities may exceed variations between cities (Briggs, 2000; Zhu et al., 2002). Some studies from the United Kingdom (UK) indicate two- to three-fold differences in $NO_2$ within distances of 50 m or less (Hewitt, 1991), while US studies suggest ultrafine particles are elevated above background concentrations until about 300 m of highways (Zhu et al., 2002).

Second, while results remain far from conclusive (English et al., 1999), sufficient number of studies have uncovered positive health effects to suggest that the exposure experience within cities may exert significant health effects. For example, a recent study from the Netherlands reported a doubling of

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cardiopulmonary mortality (relative risk (RR) = 1.95, 95% CI 1.09–3.52) near major roads in a cohort of 5000 people, where extensive control was available for confounding factors. Urban background pollution interpolated from government monitoring sites also exerted an independent effect on mortality (Hoek et al., 2002). Yet, this study used the most basic type of exposure measurement (i.e., buffers), and a need exists to test similar relationships with more robust exposure metrics.

Third, over the past 10 years, advances in GIS and associated statistical techniques have expanded into the field of exposure analysis (Collins, 1998; Melnick, 2002). These technological and methodological innovations have fuelled research on intraurban exposure because what would have been previously impossible or taken many years to accomplish can now be done in weeks to months. Coupling of dispersion, atmospheric, and time-activity models with GIS capabilities has led to even more sophisticated attempts to characterize intraurban exposures (Kramer et al., 2000; Mukala et al., 2000).

To date, there have been no published reviews of models for assessing intraurban exposure. In an effort to fill this gap in the literature, we have identified six classes of models for deriving intraurban exposure assignment, including: (i) proximity-based assessments (e.g., Venn et al., 2000); (ii) statistical interpolation (e.g., Jerrett et al., 2001a); (iii) land use regression models (e.g., Briggs, 2000; Hoek et al., 2001); (iv) line dispersion models (e.g., Bellander et al., 2001); (v) integrated emission-meteorological models (AMD and NOAA-EPA, 2003); and (vi) two classes of hybrid models, the first combining personal or household exposure monitoring with one of the preceding methods (Kramer et al., 2000; Zmirou et al., 2002) and the second combining two or more of the preceding methods with regional monitoring (Hoek et al., 2001).

We have organized this paper into three main sections. First, we systematically review literature on models for intraurban exposure assessment under the typology of the models above. We also enrich this review with applied examples from Hamilton, Canada. Second, we present a qualitative evaluation of the models based on key criteria important to health effects assessment. The paper concludes with a discussion of priorities for future research.

## Methods

The literature review discusses exposure models proceeding from the simple to the more complex. In most instances, progression from one type of model to another entails increased implementation costs in terms of research time, software, hardware and data requirements. These must be weighed against potential benefits in the accuracy of the results.

We used the following inclusion criteria to guide our search: (a) recent publication in a peer-reviewed journal available in the PubMed database (1997–2002); (b) testing of an empirical model using real data inputs (as opposed to a conceptual treatise); (c) some connection to exposure assessment for health studies or potential to be used in these studies, instead of a model focused purely on meteorological, traffic, or land use processes; and (d) some emphasis on intraurban or traffic-related pollution. The review is not intended to be exhaustive, but rather to identify representative examples of model type and to highlight some of the empirical findings when subsequent modelled exposures are applied to health outcomes.

Keywords beginning with "air pollution" followed by the terms: "long-term", "traffic", "asthma", "health effects", "kriging", "monitoring", and "MM5" were entered into PubMed. The search was performed for articles published in English from 1997 to August 2002. The estimated number of related articles was approximately 3100. Many of these were outside our inclusion criteria and were excluded. In a few instances, we relaxed the inclusion criteria to cover articles that were helpful in interpreting other studies or were published after 2002, but met other aspects of the inclusion criteria.

## Results

This section summarizes the results of our review by providing, for each model type, an overview of the methods, a synopsis of the applied studies using the particular method, a discussion of the outcome from applied studies, and a brief evaluation.

### *Proximity Models*

*Overview* Measuring the proximity of a subject to a pollution source represents the most basic approach in differentiating intraurban air pollution exposures. This method helps to identify relationships between air pollution and health outcomes based on the assumption that nearness to emission sources proxies for exposure in human populations. Figure 1 illustrates a typical road buffer that may be used to assign exposure to respondents from a respiratory health survey based on proximity to major roadways in Hamilton, Ontario, Canada. Respondents within a given distance would be assigned a "1", while respondents outside prespecified distance would receive a "0". Proximity estimates have been widely used to assess the exacerbation of asthma symptoms in children with the use of empirical models.

*Application* Our review examined 12 peer-reviewed papers focused on the association between road proximity and respiratory disease, lung cancer and stroke mortality with most quantified within a buffer of some predefined extent. The majority of these studies were conducted in countries


**Figure 1.** Example of binary classification within a buffering scheme for proximity models.

across Europe (van Vliet et al., 1997; Ciccone et al., 1998; Wilkinson et al., 1999; Venn et al., 2000, 2001; Wyler et al., 2000; Janssen et al., 2001; Hoek et al., 2002), one in San Diego, California (English et al., 1999), one in Los Angeles (Langholz et al., 2002), one in England and Wales (Maheswaran and Elliot, 2003) and one in Hamilton, Canada (Jerrett et al., 2002). All studies focused on the intra-urban scale, where traffic counts and distance to roads were the two main indicators of pollution exposure estimates. Nine analyses involve school children, but three surveyed adults.

Researchers often combine proximity measures with measures of road type or traffic density to differentially classify exposure based on both potential emissions and distance from source. Between studies, the exact implementation of the buffering analysis varies. Janssen et al. (2001) measured particulate matter less than 2.5 $\mu$m ($PM_{2.5}$), $NO_2$, and benzene. The measurements were taken inside and outside a group of 24 schools located within 400 m of major traffic routes. They found significant positive associations between the pollution concentration and decreasing distances to schools from major automotive routes. Wyler et al. (2000) matched traffic inventory, which included data on the average number of cars and trucks passing per hour at each participant's home address. Venn et al. (2000) used a traffic activity index. Vehicle flows were measured on roads in the vicinity of the study schools as a continuous measure of traffic density for those 1-km$^2$ grid cells containing a school. Respondents surveyed in the study conducted in 10 Italian cities were asked to answer questions about the level of traffic density and frequency of passing buses with the classification never, seldom, sometimes in a day or often in a day. Questions were limited to those living in houses with windows facing the street (Ciccone et al., 1998). Venn et al. (2001) used another method that proxies for traffic-related air pollution using continuous distance from the child's home to the nearest main road as the exposure proxy. Jerrett et al. (2002) used buffers at different distances from major roads to assess distance decay (i.e., 0–50, 51–100, and 101–150 m). English et al. (1999) implemented a traffic emissions model and combined this with circular buffers around the subjects' homes. The Langholz et al. (2002) leukemia study assigned traffic exposures to their case–control study using a Gaussian weighted traffic density assignment (Pearson and Fitzgerald, 2001). Maheswaran and Elliot (2003) measured the distance from the centroids of the respective census enumeration district to the closest major road and used this value as a proxy for exposure.

*Links to Health Effects* Research findings suggest that higher traffic counts or emissions near the residence may exacerbate asthma symptoms (van Vliet et al., 1997; Ciccone et al., 1998; Venn et al., 2000, 2001), yet little evidence supports a link between asthma onset and intraurban exposure. For example, after controlling for confounding effects such as age, sex, and race, English et al. (1999) found no evidence of increased risk of asthma in children under 14 with an increase in traffic counts. Yet among children with asthma, the number of medical care visits escalated with higher traffic counts. Conversely, Wilkinson et al. (1999) found no association between children, ages 5–14 years, within 150 m of a main road and the number of hospital admissions for treatment of asthma. For a study on adult asthma in Hamilton by Jerrett et al. (2002), women, aged 20–44 years, within 50 m of a major road were associated with a 50% increased risk of reporting asthma symptoms, but no significant association was found for males. None of the asthma studies used a prospective cohort design to assess the question on asthma formation. Consequently, these results must be viewed with this limitation in mind (cf. McConnell et al. (2002) for a cohort approach at the interurban scale).

With respect to other outcomes, the study by Langholz et al. (2002) found no association between leukaemia and air pollution. Maheswaran and Elliot (2003) reported a significant positive association between air pollution and stroke mortality.

*Evaluation* While the proximity method provides a straightforward application for the analysis of long-term exposure classification, it has considerable limitations. First, studies use a restricted number of covariates that could possibly confound the relationship between air pollution and health. Most studies of this type ignore population exposure to traffic exhaust at locations other than the place of residence, school or work (English et al., 1999), potentially leading to misclassification and biased risk estimates. Neglect of time–activity patterns runs through most of the exposure models we examined, but seems particularly problematic for methods that already discard much of the exposure information by proxying exposure with distance to source. Second, the vehicle mix may have an influence on emissions (e.g., trucks *versus* cars) (Kanaroglou et al., 2000; Gertler, 2003), and most studies have not taken this into account. Third, wind patterns and topography may violate the implicit assumption of isotropic dispersion (i.e., the same dispersion pattern in all directions) that underlies this method. Given that air pollution represents a continuous spatial process that would decay with distance away from the roadway, use of binary road buffers will confer exposure misclassification for subjects still in the actual influence zone (especially on the downwind side), but outside the buffer. Fourth, one study by Rijnders et al. (2001) has found that surrogate measures of pollution such as distance to expressway is correlated with markers of traffic pollution, but in complex environments, these basic methods may misclassify exposure when terrain and meteorological conditions modify the exposure experience. Finally, analyses that require self-reported measures of traffic exposure are subject to recall bias (Venn et al., 2000). This occurs because subjects are already concerned about traffic impacts due to the noise and other nuisance factors that emanate from roadways, although this problem applies to a relatively small number of studies, as most use objective measures that avoid self-reports.

Proximity methods may still contribute to environmental epidemiology as a form of exploratory analysis. It may be appropriate for research areas where aetiologic suspicion of effects exists, but there is little prior evidence. In other words, proximity methods may be quite useful for research questions or health effects assessment at a formative stage, where large investments in complex exposure assessments would be hard to justify. Arguably, for intraurban air pollution research on asthma and mortality, we may be nearing the end of this exploratory phase, with concurrent needs to advance toward more sophisticated methods.

Proximity buffers can also be useful for assessing distance decay in assigned health effects. These buffers can mimic a dose-response when subjects' assigned distances to emission source have similar exposure gradient characteristics. Figure 2 shows the odds of reporting asthma symptoms in Hamilton based on different distances from major roads. As evidenced by these results, we see a pattern of declining risk with increasing distance from the road, suggesting that distance from roadways proxies for pollution dose. Some models have used distance from point sources, along with other confounding characteristics, as a predictor of "raised incidence" in the point pattern of disease (Diggle and Rowlingson, 1994).

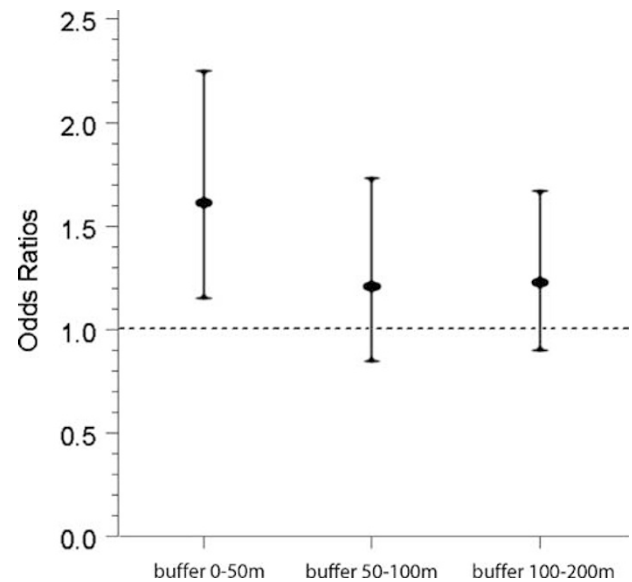


**Figure 2.** Odds ratio for proximity to roads model for females, Hamilton.

### *Interpolation Models*

*Overview* Interpolation models rely on deterministic and stochastic geostatistical techniques. Measurements of the target pollutant are obtained at a set of monitoring stations distributed throughout the study area. On the basis of this information, the objective is to generate estimates of the concentration of pollutant at sites other than the location of monitoring stations. Usually, estimates are obtained at the centre of a grid, imposed over the study area, so that a continuous surface of pollution concentration can be established. The most common geostatistical technique used in the air pollution field is "kriging" (Jerrett et al., 2001a). Kriging methods are known as optimal interpolators because they supply the best linear unbiased estimate (BLUE) of the variable's value at any point in the study area (Burrough and McDonnell, 1998). A major advantage stems from the production of both predicted values and their standard errors (kriging variance) at unsampled locations. These standard errors quantify the degree of uncertainty in spatial predictions at unsampled sites, illustrating where the interpolation is less reliable (Mulholland et al., 1998).

Kriging models exploit spatial dependence in the data to develop continuous surfaces of pollution. Beyond random error or noise in the data, spatial dependence embodies two types of effects. First-order effects, otherwise known as global trends, measure broad trends in the data over the entire study area. In contrast, second-order effects measure local variations that are a function of distance between the points (see Bailey and Gatrell, 1995; Burrough and McDonnell, 1998).

Other methods, such as splines, inverse distance weighting and Theissen triangulation rely on deterministic or geometric algorithms that may produce reasonable estimates of the pollutant at unsampled sites, but they offer no means of assessing statistically represented errors in the estimates.

These methods are simpler to apply and, in this sense, estimates obtained by them may be more appropriate in instances where the sampling network is sparse and errors are assumed to be large.

*Application* Several intraurban interpolation studies have been conducted in North America and Europe. Pikhart et al. (2001) used geostatistical modelling for the estimation of small-area sulphur dioxide ($SO_2$) levels. In a similar modelling effort, Mulholland et al. (1998) analysed the spatial and temporal distributions of ozone in the 20-county Atlanta metropolitan area using the universal kriging technique to generate concentration levels over the study area. Jerrett et al. (2001a) used this technique to model total suspended particulates (TSP) in Hamilton, Canada. A study by Abbey et al. (1999) to assess the effect of different types of air pollution on a number of mortality outcomes was conducted with a cohort of nonsmoking Californian Adventists. Using the inverse distance weighting method, they calculated relative risks based on assigned exposures. Finkelstein et al. (2003) assessed associations between air pollution and mortality using similar kriging estimates for TSP and $SO_2$ in Hamilton. Ritz et al. (2000) used a modified Theissen triangulation for a number of pollutants to assess the health effects of pollution on preterm birth in Southern California. They assigned pollution values to a zip code location only if it fell within 3.2 km (2 miles) of the air quality monitor.

When auxiliary variables such as population density, traffic emissions, or meteorological conditions are to be linked to the pollutant concentration, a technique known as cokriging can be used. This technique integrates the spatial behaviour of the pollutant and the auxiliary variable by incorporating the cross-correlation between them (Bailey and Gatrell, 1995). These advanced methods have not yet been implemented to assess health effects, but have considerable promise where sufficient data exist.

*Links to Health Effects* Overall, higher modelled concentrations of pollution seem to associate with increased respiratory health effects, mortality, or health effect modifiers. The study by Pikhart et al. (2001) examined the long-term effects on respiratory symptoms and disease in children in the cities of Prague and Poznan, Czech Republic. Their study group included 6959 school children, 7–10 years of age. Confounding factors, such as maternal smoking, type of home, sex and ages were taken into account. Ambient $SO_2$ levels were positively associated with prevalence of wheezing/whistling and asthma. Similarly, Mulholland et al. (1998) studied the relationship between modelled ozone levels and paediatric asthma exacerbation. This study continued for three successive summers — 1993, 1994 and 1995 — with ozone levels obtained from 10 monitoring stations on an hourly basis. The study subjects included paediatric (0–16 years of age) emergency room (ER) visits. To capture spatial and temporal information, the spatial average of daily zone values for the day prior to the ER visit was assigned to each patient using the zip code of the residence. Results from the study indicated an underestimation between the temporal variation in daily maximum ozone concentrations and the maximum values estimated by the kriging technique. Despite these errors, a positive association between ozone and asthma was found with a 20-p.p.b. increase in ambient ozone concentration relating to a 4% increase in the ER visit rate.

Abbey et al. (1999) found that there were a number of significant associations between different pollutions and the range of mortalities tested. Different particulate matter (PM) measures showed strong association with lung cancer in men; high PM exposure, that is, $PM_{10}$ above $100\,\mu g/m^3$, was associated with elevated natural cause, nonmalignant respiratory and cardiopulmonary mortality in men; positive significant association of lung cancer to $SO_2$ levels were found in men and women. Ozone was shown to have a significant effect on elevating risk for lung cancer in men as was $NO_2$ for women.

For a subset of subjects with age of entry similar to other cohort studies (i.e., 55–69 years), Finkelstein et al. (2003) computed an increase in nonaccidental mortality of 47% (RR = 1.47, 95% CI: 1.16–1.86) for $10\,\mu g/m^3$ $PM_{2.5}$ equivalent. TSP in this study can be converted to a $10\,\mu g/m^3$ $PM_{2.5}$ equivalent with a ratio of 25% $PM_{2.5}$ to TSP (based on assessment of 1999 pollution data supplied by the Ontario Ministry of the Environment).

Preterm births were associated with air pollution in the Ritz et al. (2000) study. A $50\,\mu g$ increase in $PM_{10}$ 6 weeks before birth was shown to cause a 20% increase in preterm birth (RR = 1.20, 95% CI: 1.09–1.33). Exposure to $PM_{10}$ early in the pregnancy increased the risk of preterm birth by 16% (RR = 1.16, 95% CI: 1.06–1.26). Assessing the effects of carbon monoxide (CO) (an increase of 3 p.p.m.) they found strong health effects only for those living inland — 13% increase (RR = 1.13, 95% CI: 1.08–1.18) in preterm birth exhibited from exposure 6 weeks prior to birth. A weaker effect was found at all locations for exposure during the first month of pregnancy (RR = 1.04, 95% CI: 1.01–1.09).

*Evaluation* The main advantage of interpolation techniques over proximity models is their use of real pollution measurements in their computation of exposure estimates. They can provide credibility to the analysis by quantifying the level of exposure difference between subjects and in computing dose–response relationships. Interpolation techniques such as IDW, spline, global/local polynomials, and multiquadratic techniques routinely cause estimation artifacts that resemble source or sinks of pollution. This can be attributed to the distance-weighting involved in these interpolation calculations. An evaluation of different interpolation techniques by Mulugeta (1996) compared interpolations created by a computer program and manually by well-trained climatologists/meteorologists and geomorphologists. Three major issues were brought to the forefront: (1) interpolation algorithms are mechanistic (i.e., they do not take other factors into account such as terrain or localized patterns in other possible predictors); (2) variability can be exaggerated with too many peaks and depressions with too high a gradient; and (3) algorithms fall apart at the edges due to lack of data. As a result, informed subjective editing may be necessary to produce a more realistic statistical surface. Data may be added between measured data points to eliminate the distance weighting or edge effects commonly produced with regular interpolation algorithms. Kriging may be a better option as much of the erroneous local variability produced with other interpolations is better dealt with by intrinsic structure of the kriging model; yet poor edge representation is still an issue.

Ordinary kriging assumes no global trend in the data and suffers the necessary disadvantage of assuming a spatially homogenous variation (called "the stationarity assumption") (Mulholland et al., 1998). According to this assumption, between sites, pollution variation within the study area is dependent on the distance between the sites and the direction of the straight line that connects the sites. Violation of this assumption may lead to estimation errors, although the technique is developed well enough to allow detection of such errors (Pikhart et al., 2001). Universal kriging, an extension of ordinary kriging, incorporates a drift function to account for a structural component in spatial variation (global trend) of the pollutant of interest, and may be of use where trends in the pollution level mix with local variation (Mulholland et al., 1998; Jerrett et al., 2001b).

A disadvantage of geostatistical interpolation relates to the availability of monitoring data. Geostatistical modelling requires a reasonably dense network of sampling sites. The number of sites for an urban area is typically in the range of 10–100, depending on the scale of analysis, scale of variability in the pollutant, local emissions, desired errors in estimates, topography of the study area, and prevailing meteorological conditions. Generally, government monitoring data come from a sparse network of stations, often selected to represent those areas most likely to be affected by industrial and heavy transportation emission sources. Reliance on government monitoring normally results in surfaces that over-smooth the true pattern of pollution and may introduce large errors in estimates over extended portions of the study, where few observations are available. This problem may be more severe in pollutants known to vary significantly over small scales such as $NO_2$, in networks with large spatial holes, or in areas with unusual topographic or meteorological variation.

Overcoming these problems may necessitate primary data collection. The high cost of primary data collection often means researchers must "grab" data for short temporal periods, which may or may not adequately represent the long-term distribution of the pollutant. In addition, researchers may be forced to rely on one or two proxy pollutants that are easily monitored, leaving key aspects of air pollution such as particles out of the mix. Thus, researchers often find themselves caught between relying on a government network with limited spatial representative strength or on their own network, which usually lacks temporal coverage.

To implement the geostatistical kriging model, the location of monitors and the digital boundary of the study area are integrated within a GIS. This requires specialized software and hardware (GIS and statistical software) as well as trained and experienced researchers to carry out the analysis. Although improvements to software such as ESRI's Arc 8 geostatistical analyst have brought the methods to a wider audience of practitioners, proper application usually requires experience with geostatistical models.

### *Land Use Regression Models*

*Overview* The land-use regression methodology seeks to predict pollution concentrations at a given site based on surrounding land use and traffic characteristics. More formally, this method uses measured pollution concentrations $y$ at location $s$ as the response variable and land use types $x$ within areas around location $s$ (called buffers) as predictors of the measured concentrations (see Figure 3). Regression mapping provides a practical approach for the assessment of exposure to traffic-related pollution (Briggs et al., 1997; Briggs, 2000; Lebret et al., 2000). The method entails the use of least-squares regression modelling to predict pollution surfaces based on pollution monitoring data and existing exogenous independent variables.

*Application* All the studies reviewed have been conducted in European cities at an intraurban scale. Two studies (Briggs et al., 1997; Lebret et al., 2000) were part of the Small Area Variation in Air pollution Health (SAVIAH) Project that examined traffic-related air pollution in four European cities (Amsterdam, Huddersfield, Prague, Poznan). A revised model described by Briggs (2000) investigates traffic-related air pollution in four UK urban areas (Huddersfield, Hammersmith and Ealing, Northampton, and Sheffield). Using similar regression techniques, a study by Brauer et al. (2003) compared traffic-related $PM_{2.5}$ air pollution models in multiple European cities. Technique has been applied to assess health effects with positive associations simililar to those found in other traffic pollution studies (Brauer et al., 2002).

In the SAVIAH study (Briggs et al., 1997, Briggs, 2000; Lebret et al., 2000), the independent variables used for the prediction of mean $NO_2$ were road traffic volume, land-use

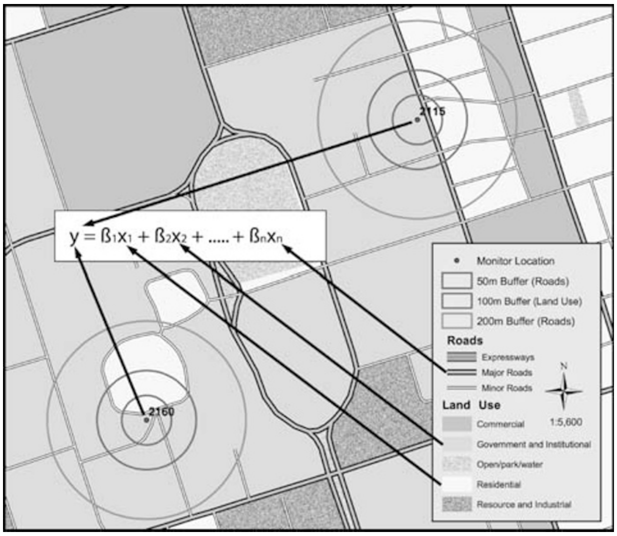


**Figure 3.** Elements of a land use regression model showing monitoring locations for $NO_2$ as the response variable and land use characteristics within buffers as the predictor variables.

type, and altitude. The relationship between the response variable and the predictors was tested for reliability from a small sample survey. A series of 8–10 reference sites were placed in each area in the SAVIAH study for validation. Briggs et al. (1997) reported good predictions for the mean annual $NO_2$ concentrations with coefficient of determination ($R^2$) values ranging from 0.79 to 0.87.

In keeping with the type of analysis used for land use regression, the study by Brauer et al. (2003) compared multiple regression analyses for $PM_{2.5}$ filter absorbance and concentration regressed against a number of traffic and population variables in several communities in the Netherlands, Germany, and Sweden. Using two sets of independent variables, they performed separate regression analyses. The first set of regressions used variables that were compiled exclusively through a GIS system, with the second adding variables to the first that were not easily obtained within a GIS framework. These variables were information gathered in the measurement-site questionnaire and included information on sampling height, street type, canyon, and type of sampling site; that is, street, rural background, and urban background. The results obtained for the Netherlands, Munich, and Stockholm in the GIS environment showed $R^2$ values of 0.81, 0.67 and 0.66 for filter absorbance, respectively. The alternate model, called their "best" model, included other variables such as traffic sites and street canyons; it produced comparable results with better $R^2$ values of 0.90, 0.83, and 0.76. Similar trends were also seen in the analysis of $PM_{2.5}$ concentration between the GIS and the "best" model. They showed that a multiple regression technique produces statistically reliable results.

*Evaluation* The main strength of LUR is the empirical structure of the regression mapping, which allows adaptation to local areas without additional monitoring or data acquisition. It also assists in methods that identify areas requiring more intensive monitoring through the installation of additional stations (Kanaroglou et al., 2003). Compared to some of the methods reviewed below, this method also has relatively low cost. The limitation of this method arises from its area-specificity, even though, as Briggs (2000) has shown, it is possible to pool effects into a random effects framework within areas of relative homogeneity of land use, meteorology, and vehicle mix.

The limits of this type of extrapolation become apparent when moving to study areas with much different land use and topography. Figure 4 illustrates the surface produced by applying Briggs (2000) Amsterdam regression coefficients from a close facsimile of Canadian land use classification to the Hamilton area. The resulting surfaces had virtually no spatial variation except around major highways, overpredicted in most areas, and produced poor correlation with measured data from government monitoring sites. Although extrapolation may be possible within similar geographic settings, that is, from urban areas with similar land use and transportation characteristics, a dense monitoring network of samples is usually required. This necessitates primary data collection with all the attendant problems noted with interpolation.

As with Brauer et al. (2003), this method can be applied to other pollutants with a suitably dense monitoring network, but the chance of collecting information on all relevant copollutants seems low due to cost and logistical problems. If investigators rely only on $NO_2$ because of the cost

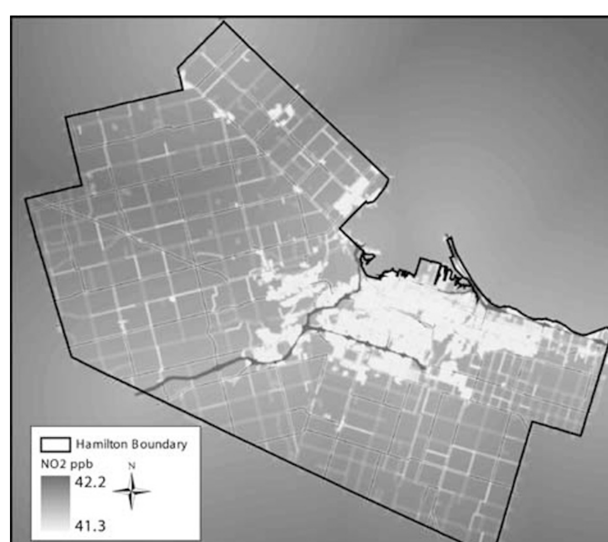


**Figure 4.** Land use regression pollution model using the Amsterdam coefficients from Briggs (2000) in Hamilton; note the lack of variability in the predicted ambient concentrations.

advantages from passive sampling with Ogawa (Rupprecht & Patashnik Co., Inc., Albany, NY, USA) or Palmes diffusion monitors, the question of whether $NO_2$ is a reasonable proxy for other pollutants arises. This issue has received scant attention in the literature, and the few studies that have examined copollutant correlations at the intraurban scale indicate only limited success (see below, under hybrid models, for more discussion).

### *Dispersion Models*

*Overview* Dispersion models generally rely on Gaussian plume equations (Bellander et al., 2001). They use assumptions about deterministic processes making use of data on emissions, meteorological conditions, and topography in estimating spatial exposure estimates of air pollution concentrations. Recently, dispersion models have been used in conjunction with GIS. This combination has allowed both information from empirical monitoring systems and data concerning the population distribution in the study area to be analysed together. With the addition of data concerning the topography of the study area, a model of the road network, and traffic observations, a more realistic representation of the problem is formed. These models have been used for different kinds of pollutants such as TSP (Bartonova et al., 1999), nitrogen oxides ($NO_x$) (Bartonova et al. 1999; Bellander et al., 2001; Nyberg et al., 2000), $SO_2$ (Nafstad et al., 2003) and CO (Benson, 1989).

In fulfilling model assumptions, dispersion models require pollution, meteorological, and emission data. Data on pollution concentrations, also referred to as background concentrations, are usually obtained from government monitoring stations near the study area and are used for model calibration (Clench-Aas et al., 1999b). Meteorological data provide information about the wind speed, wind direction, ambient temperature, solar radiation and atmospheric stability class (Gualtieri and Tartaglia, 1998). Emission data are classified into two categories, depending on the type of source: First, stationary sources account for air pollution coming from local sources such as home heating and industries. For each emission point a number of release parameters are collected (e.g., annual mass emissions, stack height, diameter, temperature, vertical emission velocity) in addition to information on facility type and location (Hruba et al., 2001). Emissions data are collected on an annual basis, or by patterns of emissions that reflect hourly rates. Second, mobile sources include traffic emissions and re-suspended particles. Traffic emissions are usually estimated by traffic counts and standard emission factors for different types of vehicles, speeds, and gradients of the road network. After the data requirements have been met and the model calibrated, the dispersion model computes the pollution levels for the desired time interval with further data updates being infrequent (e.g., changing existing point sources).

*Application* The study by Hruba et al. (2001) used the U.S. EPA's Industrial Source Complex — Long Term Model to derive ambient particulate air pollution estimates from 151-point sources and two residential area sources for Banska Bystrica in Central Slovakia. These ambient pollution values were assigned to the subjects of the Central European Study on Air Pollution and Respiratory Health in Children (CESAR) study (CESAR, 1998; Pattenden et al., 2000).

Gualtieri and Tartaglia (1998) presented a method for air pollution estimation from cars based on the estimation of traffic flows within each link of a road network. The emission model calculates emission concentration levels of typical traffic-related pollutants by means of Gaussian dispersion model estimates.

In an extensive study, also focused on traffic-related pollution, Clench-Aas et al. (1999b) developed an integrated exposure monitoring system. It expanded on an existing air quality monitoring system using dispersion modelling. The model integrates emission, meteorological and topographic data to estimate exposure at different levels (population, individuals short-term, individual long-term). The dispersion model EPISODE (Walker et al, 1999) was a part of that system, which was developed at the Norwegian Institute for Air Research. The EPISODE model was used as a basis for the exposure calculations of $NO_x$, $NO_2$ and PM as the model is capable of assessing the effects of different traffic diversion measures on health and well-being over the Oslo area. In a study also using the dispersion model EPISODE, Bartonova et al. (1999) quantified the exposure to $NO_x$ and PM in central Oslo, Norway. Estimates represented pollutants concentrations (i.e., $NO_x$ and PM) at a 1-km grid resolution.

Anderson et al. (1996), using the Integrated Model of Urban Land-use and Transportation for Environmental analysis (IMULATE) estimated CO, $NO_x$ and hydrocarbon (HC) emissions from passenger cars for all the links of the transportation network in Hamilton, Ontario. This is accomplished by first estimating traffic volumes at the link level and then using MOBILE5C through an automatic interface to translate traffic volumes into emissions. MOBILE5C is the Canadian equivalent of the emissions inventory, average speed model MOBILE5, developed by US Environmental Protection Agency. More recently, Potoglou and Kanaroglou (2002) introduced the emissions output of IMULATE to the California Line Source Dispersion model (CALINE), developed by the Department of Transportation in California (Benson, 1989). A GIS module was used to display the resulting continuous emissions surface. For illustrative purposes we provide the estimated emissions per link, emissions at CALINE receptor locations, and kernel density estimates of ambient concentrations (see Figure 5a and b for emissions per link and receptor locations from CALINE model, respectively).

The study by Nyberg et al. (2000) used the AIRVIRO dispersion model developed by the Swedish Meteorologic and Hydrologic Institute (SMHI, 1993) to assign $NO_2$ exposures and assess elevated risks to lung cancer. Bellander et al. (2001) suggests that dispersion models may be useful in the assessment of retrospective individual exposure of air pollution. In their study, reconstructed emission data of traffic and heating facilities were used with the AIRVIRO dispersion model (SMHI, 1993) to estimate NO, $NO_2$ and $SO_2$ for three points in time (1960, 1970 and 1980). These dispersion calculations were performed at four different grid resolutions. The grid resolution was higher in the city centre and decreased as it moved towards the countryside. In a follow-up study, with a population of 16,209 men with assigned $SO_2$ and $NO_2$ levels from 1974–1998 developed at the Norwegian Institute for Air Research (Gram et al., 2003), Nafstad et al. (2003) sought to find the relationship between assigned $SO_2$ exposure and lung cancer.

*Outcome and Links to Health Effects* Hruba et al. (2001) found no association between long-term exposure to TSP levels and asthma symptoms, but prevalence of nonasthmatic respiratory symptoms and hospitalizations was associated with elevated TSP.

Lung cancer was not significantly associated with modelled $NO_2$ in the study by Nyberg et al. (2000) when controlling for a number of covariates; however, elevated point estimates were found for some analyses. Bellander et al. (2001) estimated intraurban pollutant concentrations with the dispersion model and extrapolated these over time to estimate $NO_2$ and $SO_2$ pollutant levels for all years between 1955 and 1990. Using 10,800 geocoded addresses, the researchers assessed individual-level pollution exposure averages, based on indices of complex air pollution mixtures derived from house heating and traffic pollution sources. Estimated $NO_2$ values from their model correlated very well ($r = 0.96$) with site measurements. They concluded that while this technique has practical application for epidemiological studies, it might be limited to study sites that possessed historical traffic and other emission data.

In the follow-up study of 16,209 men, Nafstad et al. (2003) found an increased risk of lung cancer (RR = 1.08, 95% CI: 1.02–1.15) for a 10 $\mu g/m^3$ increase in $NO_2$ at the home address. $SO_2$ was not found to exert an influence on increasing risk of developing lung cancer (RR = 1.01, 95% CI: 0.94–1.08). They concluded that urban air pollution may increase the risk of developing lung cancer.

The resulting receptor locations, derived from the Anderson et al. (1996) study's emission estimates, were visualized by applying a weighted kernel estimate to the CALINE output to show a density of emissions in part per billion per square kilometre, as shown in Figure 6. Alternatively, the CALINE results could be interpolated as described above under geostatistical models. In either case, these exposure estimates could be assigned to subjects in a health study. Similarly, the results of the Gualtieri and Tartaglia (1998) study showed that their method could be used for pollution exposure classification.

In Norway, Clench-Aas et al. (1999c) designed the Dynamic Individual Air Pollution Exposure model (DINEX) by applying the EPISODE model to calculate concentration of $NO_2$ and $SO_2$ in an industrial area. These estimates were used to evaluate exposure at the individual scale. By using an hour-by-hour diary over two, 2-month periods, each of the 260 participants provided information used in the calculation of his/her exposure. This can be a useful technique in the estimation of personal exposure. Using the same dispersion as Clench-Aas et al. (1999c), Bartonova et al. (1999) identified the level of exposure over the residential areas in Oslo, Norway, and showed that high levels of hourly exposures were encountered near high traffic centres.

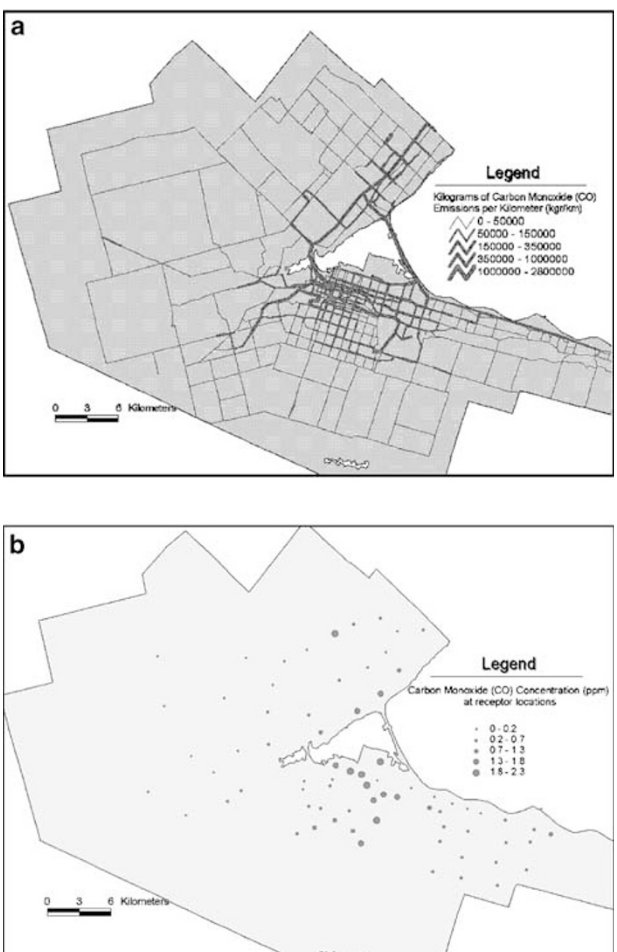


**Figure 5.** (a) MOBILE5.C-derived emission estimates using IMULATE traffic assignments for Hamilton. (b) Receptor locations created by CALINE4 for Hamilton with concentrations of CO.

*Evaluation* Dispersion models have the potential advantage of incorporating both spatial and temporal variation of air

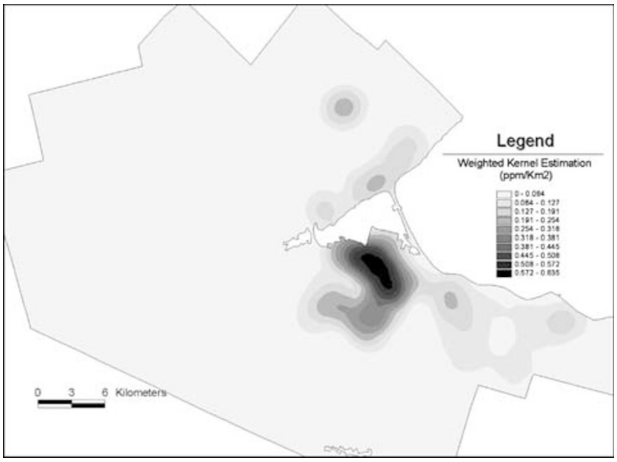


**Figure 6.** Pollution concentration computed using a kernel estimate of CALINE4 receptor locations for Hamilton.

pollution within a study area without need for dense monitoring networks (Bartonova et al., 1999; Clench-Aas et al., 1999a). Pollution concentrations vary substantially in space and time due to differences in source strength (i.e., traffic flow), wind velocity, atmospheric stagnation, and topography. All these features can be accounted for within the dispersion framework by including point and line source models for both mobile and stationary sources. Additionally, the models can be applied at different spatial scales. At the urban scale, dispersion models have been used to describe air pollution episodes, while at the regional scale they are used to assess the transfer of pollution. These models can therefore provide high-resolution analysis of patterns in health outcomes and environmental factors, and they can be applied with relatively minor alterations for different study areas (Bellander et al., 2001; Hruba et al., 2001).

The disadvantages of these models include (a) relatively costly data input; (b) unrealistic assumptions about dispersion patterns (i.e., Gaussian dispersion); (c) a need for extensive crossvalidation with monitoring data; and (d) temporal mismatches in data can possibly cause estimate errors. That is, for nontraffic and heavy diesel traffic-related emissions, a dichotomous relationship often exists between the sample interval for the two major inputs to the dispersion model — emissions and meteorology. Emissions data from point or area sources are often reported as annual emission rates, while for heavy diesel traffic, the patterns of flow do not tend to be accurately characterized by hourly traffic counts. In synergy with the inherent variability of meteorological data, which are commonly collected at the hourly time-scale, the unmeasured variability in emission sources may induce significant exposure error. Additionally, an overriding obstacle in the implementation of these models is the high level of required programming and GIS expertise coupled with fairly expensive hardware requirements.

### *Integrated Meteorological-Emission Models*

*Overview* Within integrated meteorological-emission (IME) models, meteorological and chemical modules are coupled together to simulate dynamics of atmospheric pollutants (Nicholls et al., 1993; Vogel et al., 1995; Scire et al., 1997; Byun et al., 1999; Chen and Dudhia, 2000; Pearson and Fitzgerald, 2001; Frohn et al., 2002; Tilmes et al., 2002). In these models, meteorological data are provided to the chemistry modules at every time step of the simulation. It is not necessary that chemistry modules feed back to meteorological modules (two-way coupling) because chemistry may have a minor impact on meteorological variables. IME models are useful for areas that do not have comprehensive observations to define characteristics of the key meteorological fields required for air quality application. Details of the information obtained from a coupled meteorological–chemistry model depend on the model physics, input data, grid resolution, and sophistication of land surface schemes (Otte, 2001; Yin et al., 2001).

Given their high implementation cost and data requirements, IME models have not been used for studies attempting to link air quality to health. Yet, they have considerable potential, especially for areas with large populations, where relatively small air pollution risks may exert large and high secondary pollutant levels burdens of illness and mortality. This section overviews each of the three modules and evaluates the overall potential of these models to be used in health-linked studies. IME models typically consist of three modules: meteorological, chemistry transport, and visualization and analysis.

*Application* The meteorological module provides a description of atmospheric conditions such as air motion, temperature, barometric pressure fields, cloud cover, and precipitation. These atmospheric variables serve as inputs to the chemistry module. This component is critical because it derives the transport and dispersion of pollutants in the atmosphere. A meteorological module also requires initial and boundary conditions, which are provided from observed or simulated data fields. In general, meteorological modules can be grouped into three types: diagnostic, dynamical and four-dimensional data assimilation models (Seaman, 2000).

Diagnostic models analyse observations taken at discrete points in time and space. They can also be designed to include the effects of topography. The most widely used diagnostic models are CLAMET (Scire et al., 1997) and ATMOS1 (Davis et al., 1984). Meteorological fields from dynamic prognostic models can also be the initial input for a diagnostic model.

Dynamic models integrate the nonlinear hydrodynamic equations of atmospheric motion in a numerical framework. Its components may include the following: (a) multiple-nest capabilities (b) nonhydrostatic dynamics that allow the model to be used at a higher resolution (30 s or 1 km); (c) multitasking capabilities on shared-memory or distributed-memory machines; (d) the ability to handle complex terrains; and (e) several physical parameterizations that model the major physical processes. These can account for cloud cover, radiation at the planetary boundary layer, radiation at the surface layer, and precipitation. Optimal model settings for a particular area are determined using available observed data. The most commonly used dynamic meteorological model in air quality applications is the Fifth Generation Mesoscale Model (MM5: Grell et al., 1994; Chen and Dudhia, 2000; Dudhia et al., 2000) from Penn State University/National Center for Atmospheric Research (PSU/NCAR) and the Colorado State University Regional Atmospheric Modelling System (CSU-RAMS: Pielke et al., 1992; Nicholls et al., 1993). Some recently developed dynamic models suitable for air-quality application include the University of Oklahoma's Atmospheric Regional Prediction System (ARPS) (Xue et al., 1995), U.S. Navy's Coupled Ocean-Atmosphere Mesoscale Atmospheric Prediction System (COAMPS) (Hodur, 1997), Canadian Mesoscale Compressible Community Model (MC2: Benoit et al., 1997) and Global Environmental Multiscale (GEM) model (Cote et al., 1998). The US NCAR, National Oceanic and Atmospheric Administration (NOAA), and a number of government and university scientists are developing a next-generation mesoscale forecast model and assimilation system, called Weather Research and Forecast (WRF) system (http://wrf-model.org). The system will provide a framework where the ecosystem, chemistry, and dispersion model are directly coupled to the meteorological model. It will enable real-time and predictive capabilities that will help find the fate and transport of pollutants in intraurban environments. In this way, air quality issues can be studied in combination with time activity patterns far more accurately than with the other models reviewed.

Four-dimensional data assimilation (FDDA) models combine the best features of diagnostic and dynamic approaches by integrating a numerical model that includes observed data throughout an integration period (Shafran et al., 2000). The propagation of errors in FDDA models is constrained by allowing observations to be distributed in space and time.

The second type of module implemented in the IME modelling approach is the chemistry transport module. It includes parameters regarding emissions into the atmosphere and their subsequent transport (dispersion). The strength of these emissions depends on meteorological conditions and socioeconomic activities in the area of interest. Several types of emission sources may be under consideration in the area of interest, such as point sources (factory stacks), line sources (road traffic), and distributed sources (emission from an entire city or from a natural ecosystem).

The transport or dispersion component of the IME accounts for various physical and chemical processes that transform and distribute atmospheric pollutants; it is closely coupled with the meteorological module. There are three generations of transport modules. The first deals with tropospheric air quality and with simple chemistry at local scales using a Gaussian plume formulation (Reynolds et al., 1973). The second covers a broader spectrum of pollutants and scales ranging from local to regional to urban (McRae et al., 1983; Tesche, 1983; Carmichael et al., 1986). The third generation models handle multiple pollutants simultaneously with scales reaching the continental stage, incorporating feedback mechanisms between chemical and meteorological components.

The capability for visualization and analysis is an important part of IME models supplied by the third module by providing the ability to plot data. In the visualization and analysis module, 3D animation and a graphic user interface (GUI) are becoming increasingly popular. Apart from the three major modules mentioned above, many specific models use alternate modules/programs to generate and prepare geophysical and meteorological data fields or extend specific modelling capabilities. Examples of IME modelling frameworks include United States' CALPUFF (Scire et al., 1997) and MODELS-3 (Byun et al., 1999) that have been coupled to mesoscale dynamic meteorological models such as MM5 and RAMS.

*Evaluation* IME models require high-end computational facilities, sophisticated software and highly qualified and experienced personnel for their implementation and operation. These requirements make their use a costly endeavour. Weighed against these costs are the benefits of dynamic modelling capabilities that simulate a myriad of possible exposure scenarios and the capacity to incorporate chemical transport and fate. Included in the dynamic modelling capabilities is the ability to represent complex pollutant pathways that lead to secondary pollutants, that is, ozone and secondary particles. This allows for more precise estimates of the likely pollution mix and its potential association with health outcomes.

Under specific circumstances, problems arise with the creation of an exposure data set. The output of these models is given at receptor locations which represent a quantity of pollution in location within sub areas of the larger study zone. Creating a usable exposure data set means interpolating the receptor locations between points on an array. If the array has a low resolution with few receptor locations accuracy may be greatly reduced. When points in the array are far apart and one of few receptor location lies near a point on the array, a localized interpolation artefact may be produced that resembles a large pollution source. As the number of receptor locations and points in the array are increased, the accuracy and inherent variability in the pollution can be better estimated with the interpolated pollution dataset, but in most cases the uncertainty embodied in the estimates also increases with the number of receptor locations.

More specifically, each of the three types of meteorological modules has its associated advantages and disadvantages. Diagnostic models are inexpensive to operate and require little specialized training. The major disadvantages include incomplete process representation, poor representation of airflow, and large observed data requirements. Disadvantages also include accumulation of errors over time, limited temporal coverage (up to a few days), and a highly complex system that requires extensive training. In contrast, the advantages of dynamical models include the potential for resolving regional and local-scale atmospheric circulation with no requirements for an extensive observation network. FDDA models have the advantage of including accurate meteorological data fields over a longer model integration period. This reduces the propagation of errors in a given time period, in contrast to dynamical models, making them more accurate for time periods greater than 48 h. However, the extensive computational resources and training required to implement the FDDA model type becomes its major limiting factor in comparing the three different model types.

Although promising, our review revealed that IME models have not been widely used for studies attempting to link air quality to health. The most considerable barriers to widespread implementation in the health field are the associated development time and intensive data inputs required. In addition, the 1-km grid resolution may be too coarse for air pollutants that vary at the local scale such as $SO_2$, $NO_2$, $NO_x$, ultrafine particulate matter, and CO; these pollutants can have concentration gradients over 50–100 m distances. Finally, the intensive use of computing resources and the need for expertise in meteorology and climatology may be problematic for health scientists who are often unfamiliar with the physical sciences.

### *Hybrid Models*

*Overview* The hybrid models reviewed are those that combine personal or regional monitoring with other air pollution exposure methods. The primary objective of the papers reviewed here was to compare or validate results from exposures assigned from modelling of ambient exposure with the use of monitoring at differing scales (i.e., personal and regional monitoring).

*Application with Personal or Household Monitoring* Most studies were conducted at intraurban scales in European cities, although one study was conducted in San Diego (CA, USA; Liu et al., 1997). There are four studies that use personal monitoring methods in conjunction with fixed outdoor stations to compare their difference in derived health outcomes (Liu et al., 1997; Kramer et al., 2000; Mukala et al., 2000; Gauvin et al., 2001). In these studies, personal air samplers are attached to the subjects' clothing daily at a specific time for the duration of the data-collection period. Clench-Aas et al. (1999a) estimated hourly exposure for each day based on a dispersion model, location and supplementary information provided in a daily diary. Using personal exposure measurements and daily time activity patterns, Zmirou et al. (2002) calculated a traffic-density index as a time-weighted average of traffic density-to-road distance ratio.

*Application with Regional Monitoring* Hoek et al. (2001) focused on exposure estimation by evaluating contributions at different scales. Long-term mean exposure to $NO_2$ and Black Smoke (BS) were assumed to be a function of three components: regional background, urban concentration, and local variation due to traffic. The regional background concentration was estimated by the inverse distance weighting interpolation method with use of data from a national monitoring network. Supplementary pollution from urban sources were also predicted through a regression model relating the degree of urbanization based on address density to the long-term averages of $NO_2$ and BS, an optical measure of airborne particulates, similar to the coefficient of haze (CoH), used in North America (Hoek et al. 2001). Finally, the distance to major roads is used to estimate the local traffic contributions of $NO_2$ and BS. Another study by Hoek et al. (2002) estimated total exposure from measured regional and urban background concentrations, and an indicator of distance lived from major roads. Individuals living within 100 m of a freeway and within 50 m of a major road were included in the buffer analysis.

*Outcome and Links to Health Effects* When comparing the exposure significance in these studies, we observed that personal monitoring generally provided lower concentration measurements than fixed monitoring stations. Yet personal monitors may provide a more accurate exposure estimate as indoor concentrations contribute more significantly to exposure than outdoor concentrations, as most people spend approximately 90% of their time indoors (Levy et al., 1998; Leech et al., 2002). Zipprich et al. (2002) showed that up to 68% of the variation in personal exposure to $NO_2$ could be explained by incorporating an indoor measurement into statistical models. This can be expected since the indoor measurement can account for factors within the home that may change $NO_2$ concentrations.

Mukala et al. (2000) reported that median personal measures of $NO_2$ were lower than median measures collected by other measures outside day-care centres, and Liu et al. (1997) reported that outdoor ozone ($O_3$) concentrations are four to five times higher than personal observations in the Alpine area of California. While $NO_2$ personal exposures were different across cities, they were significantly weaker than ambient background measures in three French metropolitan cites in the research performed by Gauvin et al. (2001). For children living in urban areas, Kramer et al. (2000) found that personal $NO_2$ concentrations were 50% lower than measurements from fixed stations.

These empirical models employed a mixture of multiple linear (Liu et al., 1997; Mukala et al., 2000; Gauvin et al., 2001) and logistic regressions (Kramer et al., 2000) to link exposure estimates to health outcomes. School children were the primary study groups with the exception of the work done by Liu et al. (1997), where children and adults were treated as a collective group. Children that lived in homes with gas stoves had greater $NO_2$ personal exposures than children who lived in homes with electric stoves, although no significant difference existed between gas heaters and other heating appliances (Gauvin et al., 2001). Kramer et al. (2000) found that atopy was related to outdoor $NO_2$ concentrations, but not to personal measures in 317 school children (age 9 years). Also, Mukala et al. (2000) indicated a significant relationship between personal exposure measures and coughing in 162 children (ages 3–6 years). They also reported a positive, yet statistically insignificant trend between non-personal exposures and coughing. Significant findings in this study were limited to winter months. No significant associations were found for the summer period. To obtain an accurate result of health outcomes, researchers adjusted for confounding effects in the empirical models. The health outcomes used in these studies were diverse, and not surprisingly, the confounding variables of significance were also heterogeneous. Hoek et al. (2002) reported a near doubling of cardiopulmonary mortality near major roads and highways. Thus far, this is the only published study to employ proximity road buffers as a predictor of mortality, and the results require further confirmation from other places.

*Evaluation* Using the hybrid modelling method has the advantages of measurement validation. Yet, the difficulty in implementing hybrid models depends on the combination of models being used. If a hybrid model consists of measures from existing stationary ambient monitoring sites and from personal devices as seen in Mukala et al. (2000), it can be applied with relative ease. When ambient data are unavailable, this method becomes more difficult to implement. The pollutants under study can also influence the cost and feasibility of this method. As an example, passive $NO_2$ monitors are relatively inexpensive to implement, while real-time particle monitors are prohibitively expensive.

## Discussion

In this section, we discuss our key findings by way of a comparative evaluation. Table 1 compiles the application of different models into their respective category (model type and scale of use). The integrated meteorological emission models (IME) are based on regional meteorological models and are therefore only suited to larger scale efforts. The potential exists for application to the *within community* scale for IME models by downscaling to a 1-km$^2$ resolution, but to date these models have only been applied at the between community scale. Four of the six classifications of models have been used in health effects assessment. Health effects were detected, although negative findings also appeared. Respiratory health outcomes have been tested most frequently, although cardiopulmonary, cancer, and reproductive outcomes have also been assessed. There has been limited effort to compare and evaluate formally the relative accuracy of results produced by the existing air pollution models (Collins, 1998; de Hoogh et al., 2002). Such an evaluation requires that the models be implemented with the same population over the same spatiotemporal domain.

## Empirical comparisons

Collins (1998) calculated an annual mean of $NO_2$ at eight monitoring locations that were placed permanently during consecutive survey periods. She then calculated mean pollution values from 80 monitoring sites, but excluded those eight permanent locations. This enabled comparisons of the $NO_2$ pollution surfaces estimated using kriging, hybrid and land-use regression techniques with the 80 readings at these same eight cross-validation locations. Her analysis revealed that land-use regression techniques predicted measured levels most accurately with an $R^2$ of 82%, compared to kriging and a hybrid approach with $R^2$ of 44% and 63%, respectively. Threshold pollution values from 80 monitoring sites were also compared internally for the three exposure metrics. Specifically, pollution averages in residential areas for each model were compared to this threshold value. The results were presented in the form of a percentage of residential area found to be above the estimated threshold level. Kriged values resulted in 35% of residential area above the threshold value. Regression and hybrid modelled values were 17% and 9%, respectively. A wide range in maximum and minimum values within residential areas was also apparent for each model, with kriged models estimating a range of 22–42 $\mu g/m^3$, regression models estimating 23–58, and 18–82 $\mu g/m^3$ for hybrid models. The difference between the minimum and maximum provides information with regard to the level of data smoothing, whereby the smaller ranges indicate greater smoothing.

de Hoogh et al. (2002) compared modelled concentrations of $PM_{10}$ and $NO_2$ to commonly used source–activity indicators based on traffic and road characteristics. For validation purposes, monitored pollution values were used from locations within the study cities. The exposure measures were applied to postal code locations and tested in two major

**Table 1.** Studies categorized by model type and scale of application.

| Model | Level | | |
|---|---|---|---|
| | Between community | Within community | Used in health effects assessment? |
| Proximity | | van Vliet et al. (1997), Ciccone et al. (1998), Wilkinson et al. (1999), Venn et al. (2000, 2001), Wyler et al. (2000), Janssen et al. (2001), Hoek et al. (2002), English et al. (1999), Jerrett et al. (2002), Mahesswaran and Elliot (2003), Langholz et al. (2002) | Yes |
| Interpolation | Mulholland et al. (1998) | Jerrett et al. (2001a,b), Finkelstein et al. (2003), Pikhart et al. (2001), Ritz et al. (2000), Abbey et al. (1999) | Yes |
| Land use regression | | Briggs et al. (1997), Lebret et al. (2000), Briggs (2000), Brauer et al. (2002), Brauer et al. (2003), | Yes |
| Dispersion | | Hruba et al. (2001), Clench-Aas et al. (1999b), Walker et al, 1999), Bartonova et al. (1999), Anderson et al. (1996), Potoglou and Kanaroglou (2002), Benson (1989),Bellander et al. (2001), SMHI (1993), Gualtieri and Tartaglia (1998), Nyberg et al. (2000), Nafstad et al. (2003) | Yes |
| Integrated Meteorological Emissions | Nicholls et al. (1993), Vogel et al. (1995), Scire et al. (1997), Byun et al. (1999), Chen and Dudhia (2000), Pearson and Fitzgerald (2001), Frohn et al. (2002), Tilmes et al. (2002) | Possible application scale with downscaling of models to 1 $km^2$ | No |
| Hybrid: personal or regional exposure plus one of models above | | Liu et al. (1997), Kramer et al. (2000), Mukala et al. (2000), Gauvin et al. (2001), Clench-Aas et al. (1999c), Zmirou et al. (2002), Hoek et al. (2001, 2002) | Yes |

urban areas in the UK. Percentages of postal codes classified in the same exposure quintile were calculated for all exposure measures. In comparing the proximity measure and regression approach 30% were classified in the same quintile, while 26% of the sites were similarly classified for proximity and dispersion approaches. When comparing regression and dispersion approaches for $NO_2$, only 30% of the postal codes were classified within the same quintile. The highest comparability was observed at 68% for dispersion modelled $NO_2$ and $PM_{10}$. Obvious differences were found between the exposure measures; however, modelled and monitored concentrations showed consistently strong correlations for both pollutants. This correlation implies that modelling can provide a reliable assessment of long-term $NO_2$ and $PM_{10}$ concentrations. These comparisons emphasize the potential differential impacts related to the choice of air pollution exposure measures, especially if used as a basis for related health effects.

## Comparative evaluation

Although these comparative studies fill an important gap, the emphasis on correlations between various methods leaves many other important evaluation criteria unaddressed. Thus, we offer a synthesis of the various methods based on comparative criteria that may assist others in deciding as to which method suits the needs of their specific study design best. Table 2 summarizes the results of this evaluation. Each row of the table corresponds to one of the models. From the top to the bottom row of the table, models are arranged in terms of increasing complexity with respect to the suitability, requirements, and the cost for their implementation. Each column corresponds to a different evaluation criterion; the first class of criteria concerns the matching of the method conceptualization to theory and the utility of the model/methods to respiratory studies. Specific requirements, such as the amount of data, the need for data updates and the software/expertise required, form a second class of criteria. The third class of criteria includes the overall implementation cost and marginal benefit of implementing one model relative to a base model.

The overall implementation cost is measured in three parts: (a) equipment cost, which includes the cost of monitoring devices (e.g., personal monitors, monitoring tubes), as well as computer hardware, which can be taxing for some of these models; (b) many of these models require sophisticated

**Table 2.** Example of binary classification within a buffering scheme for proximity models.

| Model | Theory concept match | Limitations to health studies | Data requirements | Need for updated data | Software/expertise | Overall implementation cost | Marginal benefit | Transferability |
|---|---|---|---|---|---|---|---|---|
| Proximity based | Low | Crude exposure estimates | Traffic volumes<br>Distance from line source<br>Questionnaire | Low | GIS<br>Statistics | Equipment: low<br>Software: low<br>Personnel: medium | Base case | Low |
| Geostatistical | Medium | Depends on density of the monitoring network | Monitoring measurements | Low | GIS<br>Spatial statistics | Equipment: medium<br>Software: medium<br>Personnel: low | Transferability<br>Error structure of estimate | Low |
| Land Use regression | Medium | Depends on density of observations | Traffic volumes<br>Land-use<br>Meteorology<br>Monitoring measurements | Medium | GIS<br>Statistics<br>Monitor experts | Equipment: medium<br>Software: medium<br>Personnel: medium | Transferability<br>Error structure of estimate | Medium |
| Dispersion | Medium | Extensive inputs<br>Unrealistic assumptions about pollutant transport | Traffic volumes<br>Emissions from point sources<br>Meteorology<br>Monitoring measurements<br>Topography | Medium | GIS<br>Statistics<br>Monitor experts<br>Dispersion software | Equipment: high<br>Software: high<br>Personnel: medium | Emphasis on process | High |
| Integrated meteorological emission | Medium | Coarse resolution | Traffic volumes<br>Emissions from point sources<br>Meteorology<br>Monitoring measurements<br>Topography | High | GIS<br>Statistics<br>Monitor experts | Equipment: high<br>Software: high<br>Personnel: high | Emphasis on Process | Medium |
| Hybrid (personal monitoring & one of the preceding methods) | High | Small and biased sample<br>Depends on combination | Questionnaire<br>Personal monitoring data<br>Other depending on combination | Depends on combination | Personal monitor experts<br>Survey design<br>Depends on combination | Equipment: high<br>Software: *<br>Personnel: *<br>*Depends on combination | Depends on combination | Low |

computer software, such as visualisation, GIS and spatial statistical packages, which may add significantly to the implementation cost of the study; and (c) personnel costs, which may include survey specialists, monitoring equipment experts, spatial analysts, and computer programmer/analysts.

The marginal benefit evaluates all models relative to the "proximity models," which are taken here as the base case. The time required for the implementation of a model is also an important criterion that may be included in this class. Model implementation time varied significantly in the examined literature, depending on data availability and collection method. In some instances, especially when the design of the study required that data be collected for different seasons of the year, the implementation time of the project was long (i.e., greater than 2 years). Because of the lack of a common basis for comparison between projects, we have decided against including model implementation time as one of the evaluation criteria. The last criterion we include in Table 2 under the term "transferability" is the possibility of transferring the results of a model or an estimated statistical model to other locations. In this case, high transferability means that the model can provide reliable results if implemented with minor adjustments at a different location.

Proximity models usually provide a relatively crude but quick evaluation of the impact that traffic pollution has on respiratory symptoms. The main disadvantage of such models is that parameters affecting the dispersion and physicochemical activity of pollutants are not considered. These models are limited to the statistical investigation between traffic activity and the possible risk of illness or death. Statistical and GIS tools are often used to assess traffic volume on the relevant road network and the distance of subjects from the road network. In addition, survey data are collected from the population under study. The time to develop a proximity model is generally short if the necessary data are available. These studies may have to be repeated at different time periods to capture seasonal variation in traffic.

Geostatistical models can be implemented in conjunction with a dense, well-distributed, monitoring network. These models allow the estimation of pollution concentration over several time intervals, but this is limited only by the number of available measurement periods. Often the estimated surface of a pollutant over a study area is used in conjunction with socioeconomic data and population density to assess risk for a specific study group. Improved hardware, spatial statistics software, and appropriate expertise are mandatory for the implementation of a geostatistical model, thus increasing the cost relative to a proximity model.

Land-use regression models are relatively inexpensive to implement and can provide reliable estimations of traffic-related air pollution when adequate land use, transportation, and pollution monitoring data are available. In most cases, greater reliability is achieved when the number of observations over the study area is increased. These techniques may also employ of independent variables known to significantly affect the concentration of pollutants. Such variables are land-use, elevation, and traffic conditions. The cost can be higher than both of the previous methods, especially if one seeks a dense set of observations in traffic flow and other parameters.

Dispersion models and IME models are considered more sophisticated and reliable than the previous models, but are more expensive to implement. These models can be used at the regional and the intraurban scale. They require a substantial amount of data on emissions and meteorology. Improved management tools, specialized software (GIS, dispersion software, integrated software) and computer hardware are capable of handling, storing and processing these data. Furthermore, there is a need for specialized personnel in GIS, statistics, mathematics, and computer science. Thus, the cost of implementation is significantly higher than with previous models. The compensation comes in the form of a better representation of the process under study. The main difference between dispersion and integrated models is that the latter incorporates a chemical and meteorological module to simulate the dynamic mobility of atmospheric pollutants in a multi-step simulation process. As a result, integrated models demand increased computing power and specialized personnel. A further drawback of such models is that their results have a coarse spatial resolution, making their application to exposure studies problematic (usually a 1-km prediction grid is the maximal downscaling available). It is possible to improve on the resolution of the results only at the expense of significantly increased data requirements and associated computer processing power.

Personal monitoring offers the most direct way of measuring the exposure of subjects to air pollutants. The drawback of such models, however, is the high cost of implementation and the associated small number of observations that tends to produce sample biases. Only specific types of subjects will carry monitors and record their daily activities for a relatively prolonged time period. For this reason, personal monitoring is often used as a complement to one of the other model types, creating what we have termed "hybrid models." These hybrid models are associated with a high theory-to-concept match because they allow direct exposure measurements. In the absence of subjects willing to partake in a personal monitoring program the use of regional monitoring in conjunction with another modelling schema allows the researcher to create additional validation for their model (i.e., combining two or more modelling results).

## Future directions

In reviewing the current state of knowledge for intraurban air pollution exposure assessment, we found a growing emphasis on increasingly sophisticated land use, dispersion, and integrated meteorological models. These have now entered the mainstream of air pollution health effects assessment, and they will probably replace less robust buffering and proximity methods over the next 5 years, except perhaps in early phases of previously unexplored health effects.

Beyond refinements in these models, we also emphasize a need for more research in three areas: (1) remote sensing models, (2) mobility or activity–space analysis, and (3) personal monitoring to crossvalidate estimates and improve understanding of the role that measurement errors play in risk assessment models.

First, the use of remote sensing for exposure assessment appears to be a promising avenue for future research, particularly in low-income countries that may lack the resources to implement extensive ground monitoring programs. This method of exposure assessment usually relies on high-resolution satellite observations in combination with existing fixed-site monitoring stations. The method determines the aerosol optical thickness by classifying consistent spectral images with pollution cover over urban areas and then cross validating and reclassifying values with "virtual stations" that have similar land use and transportation characteristics (Ung et al., 2001). Our review identified only a few of these studies, and none had been used specifically to assess health effects or inform regulatory decisions. Although promising, these remote sensing methods remain formative and often require simplifying algorithms and ground truth data to reduce computation demands and increase accuracy of pollution estimate (Kanaroglou et al., 2002). Currently, the methods available seem better able to detect the presence or absence of pollution, rather than classifying what type of pollution is present. The methods also lack an accepted means of assessing errors in estimates. Despite these limitations, the relative availability of remote sensing data and improvements in computational techniques will contribute to practical and methodological advancements, meriting future use in health effects studies.

Second, while researchers have expended considerable effort on characterizing the spatial and temporal distributions of air pollutants at the intra-urban scale, much work remains in understanding the role of individual mobility in conditioning exposures. Time–activity studies have illuminated relatively consistent patterns of activity between different populations, with individuals spending an average of about 66% of their time at their residential location (Leech et al., 2002), but these studies have not done enough to investigate the crucial question of "where" individuals are the rest of the time. Do they commute long distances? Do they tend to have social activities at short or great distances from their homes? Does the time they spend outside tend to coincide with temporal peaks in air pollution (e.g., late day rush hour ozone levels and children playing after school)? These and other related questions remain largely unanswered. Potentially, collaborations with transportation experts who specialize in the analysis of "activity spaces" may lead to rapid answers for these questions (Axhausen et al., 2001).

Third, to assess external validity of these new measures, more cross-validation against personal exposure measurements will be needed. Many of the personal monitoring studies have assessed personal measures against central monitors with two important results: (a) individual personal monitoring estimates correlate poorly with central monitors (Gauvin et al., 2001), but (b) when these personal estimate are averaged on a daily basis, they correlate highly with central monitor estimates (Mage et al., 1999). Thus, while central monitors may supply reasonable proxies for time-series assessments over the entire population, they probably provide poor estimates of personal exposure for chronic studies. Answering this second question through comparisons of exposure metrics against personal monitoring at the intraurban scale will contribute to chronic health effects assessment by disentangling the role of measurement error for different subjects in a given health study. A need also exists to compare different exposure estimates within the context of actual health outcome studies. This, too, will increase knowledge on how exposure measurement error may influence health effects assessment.

The overarching question of what methods are most appropriate for which circumstance cannot be fully answered until the issues of time–activity and measurement error are better understood. In cases where the key question relates to the size of the effect, more sophisticated hybrid models may be warranted. For example, because researchers have already demonstrated significant associations between relatively simple metrics such as road buffers and childhood respiratory health outcomes, the question now becomes, "are the effect sizes accurate." More refined models of exposure may shed light on this question, given the bias toward the null effect induced by measurement error. Researchers may also be interested in which pollutant in the complex mixture around roadways exerts the health effects when basic relations have already been demonstrated. Similarly, more refined models may be necessary to assess health effects in subgroups. Limited power to detect effects in these groups may necessitate lower exposure measurement error. As mentioned earlier, for more formative hypotheses, basic models may provide a reasonable starting point, but a risk of a false negative finding cannot be easily dismissed because error may bias toward the null or increase the variance on the dose response function (Lebret, 1990). In early studies, researchers may find it useful to focus on whether they observe a dose–response function based on distance from source or other empirical experiments that may give clues about possible associations.

Much of the desirability of a given model for a specific study or health outcome will also depend on available or potential data supports. Advanced dispersion and integrated emission models (IEMs) will likely perform poorly when requisite data support are lacking. Although these models have theoretical elegance, researchers may find more robust results from land use regression or geostatistical models when the data support for IEMs is weak. IEMs in particular may take some time and simulation or validation testing to produce reliable and valid results as the intraurban scale. Again, these data considerations impede overall conclusions beyond general advice that, as with many spatial models, the sophistication of the model must match the resolution of the data. While this may seem obvious, we believe cautionary advice is warranted given the potential of many models to produce visually appealing results and exposure maps that go well beyond the available data accuracy or resolution.

In sum, the advent of new GIS and modelling methods for intraurban exposure assessment has emerged at a time when the interest in chronic health effects assessment has increased. The coincident timing of these two events will probably lead to rapid increases and advances in methods for assessing exposure at the intraurban scale. Hybrid models combining different methods with personal monitoring appear well suited to overcoming the conundrum of achieving population representative samples while understanding the role of exposure variation at the individual level. Remote sensing and activity–space analysis will complement refinements in pre-existing methods, and the field of exposure assessment may help to reduce scientific uncertainties that now impede policy intervention aimed at protecting public health.

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