MODELLING THE INTRA-URBAN VARIABILITY OF AMBIENT TRAFFIC POLLUTION IN TORONTO, CANADA

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ABSTRACT

The objective of the paper is to model determinants of intra-urban variation in ambient concentrations of nitrogen dioxide (NO_2) in Toronto, Canada, with a land use regression (LUR) model. Although researchers have conducted similar studies in Europe, this work represents the first attempt in a North American setting to characterize variation in traffic pollution through the LUR method. NO_2 samples were collected over two weeks using duplicate two-sided Ogawa passive diffusion samplers at 95 locations across Toronto. Independent variables employed in subsequent regression models as predictors of NO_2 were derived by the Arc 8 geographic information system (GIS). Some 85 indicators of land use, traffic, population density, and physical geography were tested. The final regression model yielded a coefficient of determination (R^2) of 0.69. For the traffic variables, density of 24-hour traffic counts and road measures display positive associations. For the land use variables, industrial land use and counts of dwellings within 2000 m of the monitoring location were positively associated with NO_2. Locations up to 1500 m downwind of major expressways had elevated NO_2 levels. The results suggest that a good predictive surface can be derived for North American cities with the LUR method. The predictive maps from the LUR appear to capture small-area variation in NO_2 concentrations. These small-area variations in traffic pollution are probably important to the exposure experience of the population and may detect health effects that would have gone unnoticed with other exposure estimates.

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INTRODUCTION

Policymakers and scientists have shown growing interest in the health effects of chronic exposure to ambient air pollution. Traffic-related air pollution is of particular interest from a regulatory perspective because the demand for transportation will probably outpace improvements in vehicle technologies over the next decade (Delucchi, 2000). European studies reporting large health effects for persons living close to major roads have also heightened concern about traffic pollution (Hoek et al., 2002). In spite of the interest in traffic pollution sparked by these coalescing concerns, uncertainties in exposure assessment methodologies continue to raise questions about the reliability and accuracy of risk estimates from chronic air pollution studies. This scientific uncertainty impedes efforts by policymakers to implement effective traffic pollution control programs.

In this context, it was sought to model determinants of intra-urban variation in ambient concentrations of nitrogen dioxide (NO_2) in Toronto, Canada, with a land use regression (LUR) model. NO_2, an important inorganic gas, serves as a good indicator of intra-urban traffic pollution (Niewenhuijsen, 2000). Although researchers have conducted similar studies in Europe, this work represents the first attempt in a North American setting to characterize variation in traffic pollution through the LUR method.

Background

LUR employs the pollutant of interest as the dependent variable and proximate land use, traffic, and physical environmental variables as independent predictors. Thus the methodology seeks to predict pollution concentrations at a given site based on surrounding land use and traffic characteristics. Specifically, this method uses measured pollution concentrations (y) at locations (s) as the response variable and land use types (x) within circular areas around s (called buffers) as predictors of the measured concentrations (see Figure 1). The incorporation of land use variables into the interpolation algorithm detects small-area localized variations in air pollution more effectively than standard methods of interpolation such as kriging (Briggs et al., 1997; Briggs et al., 2000; Lebret et al., 2000).

To date, LUR studies of criteria air pollutants have been conducted exclusively in Europe. 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). An updated model described by Briggs et al. (2000) investigates traffic-related air pollution in four United Kingdom (UK) urban areas (Huddersfield, Hammersmith and Ealing, Northampton, and Sheffield). The independent variables used for the prediction of mean NO_2 were road traffic volume, land-use type, and elevation. These variables produced good predictions with coefficient of determination (R^2) values ranging from 0.79 - 0.87.

More recently, Brauer et al. (2003) compared traffic-related $PM_{2.5}$ air pollution models in multiple European cities using the LUR technique. In each of the study cities, investigators fit two types of models: one available through a geographic information system (GIS) environment and another that included additional variables not available in the GIS. The results obtained for the Netherlands,[6] Munich, and Stockholm in the GIS environment showed R^2 values of 0.81, 0.67 and 0.66 for particle filter absorbance, respectively. The alternate model or "best" model included variables such as high traffic locations and street canyons. This model produced results with better R^2 values respectively of 0.90, 0.83, and 0.76.

Although no North American studies are directly analogous to the European studies, one American study has used the LUR approach to model variability in carbon dioxide (Wentz et al., 2002). This study was more concerned with understanding the land use and vegetative characteristics associated with this greenhouse gas rather than assessing exposures directly related to health effects. The results were more modest than in the European studies discussed above, with R^2 values ranging from 0.54-0.74. These results raise questions about whether the LUR method will perform adequately in North American cities, particularly for traffic pollutants such as NO_2 that display significant variation over scales as small as 50 metres (Hewitt, 1991).

[6] Multiples sites across many cities in the Netherlands, too numerous to mention, were sampled for this study.

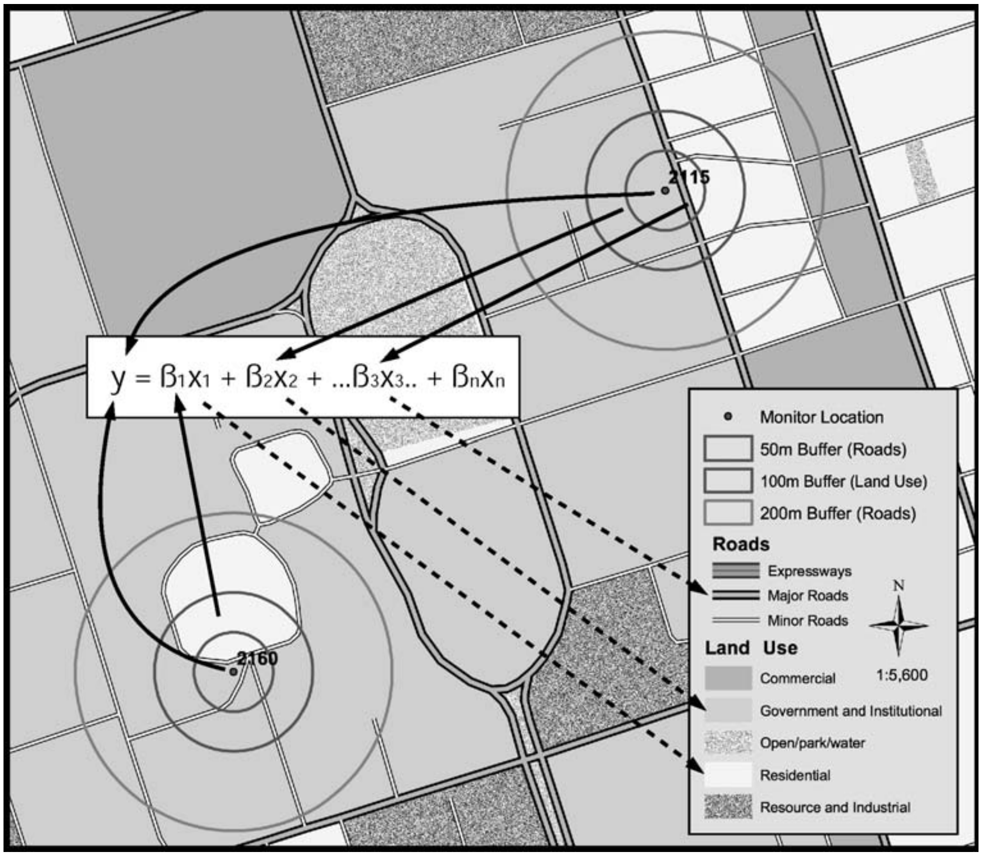

Figure 1: Elements of a land use regression model showing monitoring locations for NO_2 as the response variable and land use characteristics within buffers as the predictor or independent variables.

In addition to these empirical results, other differences in land use and traffic distinguish newer North American cities from those in Europe that evolved earlier into major conurbations. Fowler (1992) outlines these land use and transportation characteristics as deconcentrated, decentralized, large scale, homogenous and segregated. Compared to European centres, North American cities overall have lower population densities (deconcentrated), and a greater proportion of the population lives in suburban areas outside the city centre (decentralized). Moreover, cities in North America tend to have land use developments that occupy large tracts of land for single land use types, making their land use homogenous and large-scale (e.g., large residential subdivisions of many thousand houses, huge commercial shopping centres, and large industrial zones). And, individual land use types are segregated from each other creating a need for automotive travel between commercial and residential areas. All of these factors contribute to higher levels of automobile use (Newman and Kenworthy, 1989), energy consumption (Hough, 1995), and subsequent higher levels of pollution emissions. Each of these contrasts raises questions about the applicability or adaptability of the LUR methods developed in Europe to North America.

METHODS

This section outlines the study setting, the data sources used in the analyses, and the methods used to estimate NO_2 concentrations. NO_2 measurements are technically "mixing ratios," not concentrations, as these values do not incorporate a mass weight. For ease of reading and by convention, the wording concentration has been used in the remainder of this article.

Study Area

Toronto is the provincial capital of Ontario and Canada's largest city (estimated population: 2.6 million people, Statistics Canada, 2001; approximate area: 633 km^2). It is located on the north shore of Lake Ontario (situated at 43^o 39' N, 79^o 23' W) with a climate classified in the "Humid East" region of temperate North America (Getis and Getis, 1995). Similar to other large cities in North America, many expressways traverse the Toronto landscape, including some of the busiest in North America (e.g., Highway 401 has peak flows of about 400,000 vehicles per day).

Data - Measurements and Preparation of the Dependent Variable (NO_2)

NO_2 concentrations were measured for a two week period from September 9 to 25, 2002 at 100 locations across Toronto. NO_2 was selected to proxy for traffic related air pollution because it is relatively inexpensive to measure and has been used widely as a metric of exposure to traffic emissions (Briggs et al., 1997). To capture small-area variation in the NO_2 concentrations, 100 sampling locations across the city were used. NO_2 may display significant differences on scales as small as 50 m (Hewitt, 1991), and hence a dense monitoring network is needed to measure these small-area variations. This number is in line with the study by Lebret et al. (2000), that used between 70 and 80 NO_2 monitors for measurements in Amsterdam, Netherlands (land area of 25km^2), and Huddersfield, UK (land area of 300km^2), considering Toronto has a larger land area of 633km^2. Sampling locations were selected using a population-weighted location-allocation model based on potential NO_2 variability and the density of children aged 0-6, as this exposure assessment represents the first stage of a childhood asthma study (Kanaroglou et al., 2003). The outcome of using a location-allocation model is a sampling network that better captures the inherent variability in city-wide exposures.

Ogawa™ passive samplers were used to measure concentrations of NO_2. Two-sided samplers were deployed in pairs (yielding four observations per site) at a height of 2.5 meters because this was the first time that Ogawa NO_2 monitors were used for this type of ambient monitoring. The deployment of samplers took less than 72 hours. All samplers were removed 14 days after their installation. The nitrite content on collection pads was determined by ion chromatography (Gilbert et al., 2003). For each location, the arithmetic mean, standard deviation, and coefficient of variation of NO_2 results were calculated.

Only five of the 100 samplers deployed were removed due to vandalism or invalid measurements, leaving 95 observations for analysis. Figure 2 illustrates the locations of these 95 monitors against the backdrop of different land uses. Additionally, one more sample was removed from the analysis. It was a significantly high outlier, which further investigation revealed the presence of an active construction site in proximity to the monitor over the sampling period.

Collected NO_2 data were then checked thoroughly for consistency and reliability prior to analysis. There were two criteria used for this initial assessment. First, each site had to have at least two valid measurements. Sites with only one valid measurement were excluded from the analysis, as there was no means to verify the concentration observed with duplicate observations. Second, the coefficient of variation among observations at a given site (COV = *standard deviation/mean*) had to be less than 0.25 to count as valid. If the COV was greater than 0.25, then the observation that created the greatest amount of variability was removed and the first criterion was applied again. For cases with COV of 0.25 or greater, this process was performed until there were only two measurements remaining at each location. If COV remained greater than 0.25, then the entire sampling location was discarded.

As an initial exploratory procedure to determine overall trends and local autocorrelation in the NO_2 data, ArcGIS 8 software (ESRI Corp, Redlands, CA) was used to implement the geostatistical interpolation method known as 'kriging' (using the spherical model). After examining these general patterns in the data the LUR model was developed.

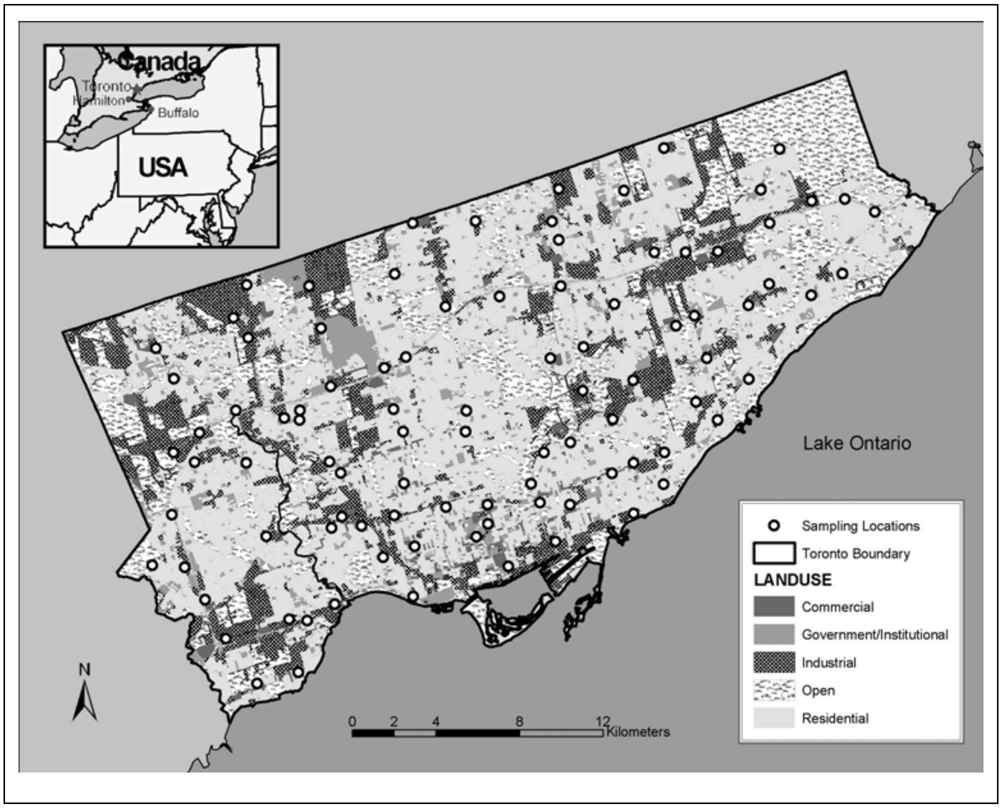

Figure 2: Toronto sampler locations against a backdrop of land use classification.

Data for Independent Variables

In total, 85 independent variables, or variations of different variables, were created with these data using ArcGIS 8 (see Appendix 1 for the complete list of variables tested in the analysis). The variables were grouped into five broad categories: (1) land use (area of different land uses within buffers of various radii around each sampling location); (2) road and traffic (lengths of different road types and traffic flow counts within buffers of different radii); (3) population (population density, density of dwelling units, average dwelling values); (4) physical geography (geographic location in terms of X and Y coordinates, and elevation); and (5) meteorology (wind direction in relation to major emission sources).

Toronto land use and road network data were acquired from a commercial source (i.e., DMTI Spatial Inc., Markham, ON, Canada). Average daily expressway or highway traffic counts were obtained from Environment Canada, and the City of Toronto Information Services provided similar data for major roads throughout the city. Population data were compiled from the Statistics Canada 1996 Census of Population (these were the most recent data available in GIS format). A digital elevation model developed by the Ontario Ministry of Natural Resources was compiled through ArcGIS 8.2 at a 5-metre resolution. Meteorological data were obtained from a network of 15 surface observation stations operated by various government agencies and private organizations in the Toronto region, including Meteorological Service of Canada, Ontario Ministry of Environment, and Ontario Power Corporation. The configuration of the network defined a modelling domain of some 8000 km^2. This ensured an interpolated (and not an interpolated-extrapolated composite) wind field prediction by maintaining a variable-width (22-35 km) buffer of data points around City of Toronto's footprint, thereby reducing the likelihood of erroneous prediction.

In total, 17-day (September 9-25) average zonal (E-W) and meridional (N-S) orthogonal components of wind – *u* and *v*, respectively – for the 17:01-18:00 segment of the day were calculated for each station. This hour not only represents the daily afternoon peak traffic flow for the 17 days period that the samplers were deployed, but it is also representative of the overall prevailing wind patterns. The orthogonal components were then used, following Goodin et al. (1980), as urban wind field datasets to assess the pollution-wind relationship.

An interpolation method found to be well suited for modelling vector fields – the Radial Basis Functions (RBF) Multiquadric (MQ) method – was used for wind field construction. MQ interpolation has been used in meteorology and in related disciplines for more than 30 years (e.g., Shaw and Lynn, 1972; Lynn, 1975; Sirayanone, 1988; Nuss and Titley, 1994; Hubbe et al., 1997) The *u* and *v* components of wind were interpolated as separate scalar entities, which then allowed for wind direction vector calculations to be performed within the ArcGIS framework, with the ultimate goal being the determination of the upwind-downwind relationship between the high traffic expressways and the wind direction. To determine this relationship, the interaction between two vector sets is obtained by applying the dot product operation:

$$\mathbf{a} \cdot \mathbf{b} = a_1 b_1 + a_2 b_2 = |\mathbf{a}||\mathbf{b}|\cos\theta \quad \text{(eq.1)}$$

Where **a** and **b** are the direction vectors with components a_1 and a_2 and b_1 and b_2, representing the direction to the nearest expressway and wind direction, with θ the angle that lies between two of them. This second part of the equality in equation 1 is an identity that provides two pieces of information: (1) the angle that accounts for the degree of relationship between the wind vector and expressway, and (2) the sign of $\cos\theta$ shows whether an expressway lies up or down wind of any specific point of interest in study area for that particular wind field. A negative value translates into a grid cell located downwind of an expressway. The opposite is true for positive values – grid cells are located upwind of an expressway.

RESULTS

The 94 NO_2 samples used in the analysis had an arithmetic mean of 32.2 ppb, with values ranging from 17.4 to 61.1 ppb (SD = 9.2). There were 19 samples that had a value greater than one standard deviation from the mean, i.e. greater than 41.4 ppb. Of these, 15 were located in proximity to expressways with the remaining 4 located within heavily trafficked corridors. Very good agreement was found between the paired Ogawa samples.

Model Selection

The NO_2 measurements were transformed with the natural logarithm because of a strong right-skew. Each of the 85 independent variables were tested through an individual bivariate regression model with SPSS 11.5. This identified variables that were highly correlated with the NO_2 observations. Appendix 1 shows the R^2 and t-score results from each bivariate analysis. Overall, the traffic and road length variables displayed the strongest association with NO_2 concentrations. Specifically, the density of roads within a 300-metre radius buffer of each sampler location (Rd_density) produced the best bivariate model, with a t-score of 7.03 and an R^2 of 0.35.

In the following step, the Rd_density variables were paired with other significant variables in a series of trivariate regression models. This series of analyses identified the pairing with population density (as calculated through a kernel estimate with population-weighted enumeration area (EA) centroids, and a 2000-m search radius (EA2000)), as the best two-variable combination for predicting NO_2 exposures. The process of manual forward stepwise regression was performed until five independent variables were included in the model. Although useful for exploration, the results were hampered by high levels of collinearity between the variables.

Other variable combinations were also tested with various "best subsets" regression analyses in Minitab 12.22. Best-subsets regressions generate regression models with the "best" R^2 values, mean square error predictions, and the Mallow Cp statistic, which is an indicator of how well the model fits the data without introducing bias (Hamilton, 1992). Due to limitations on the number of variables allowed by the software in each selection, the best subsets were limited to the most significant variables discerned through the bivariate and manual stepwise screening. Wind direction variables were added to the parsimonious model selected from the above procedures because the wind models and data took considerable time to construct.

After determining the appropriate model, standard regression diagnostics were applied to assess problems such as outliers, heteroskedasticity, and spatial autocorrelation. A series of cross-validation tests were also completed to assess the predictive capacity and stability of the final set of models used in the analysis.

Table 1 shows the model for predicting intra-urban variation in NO_2. This model produced an R^2 of 0.69. Each individual variable has a significant t-score and acceptable multicollinearity, as demonstrated by the Variance Inflation Factors (VIF). All of the coefficients have the expected signs. For the traffic variables, density measure of 24-hour traffic counts (TRAF500) and road measures (RD2_50 and RD1_200) display positive associations. For the land use variables, industrial land use (IND750) within 750 m, and counts of dwellings within 2000 m (DC2000) of the monitoring location were positively associated with NO_2 concentrations. Locations up to 1500 m downwind of major expressways (D_WIND15) had elevated NO_2 concentrations. A trend was observed in the data with higher NO_2 concentration values in the west to lower values in the east (X).

Table 1: Summary of the regression results for the logarithmic NO_2 Model.

Source	SS	df	MS		
				Number of obs =	94
				F(7,87) =	27.4
Regression	5.09	7	0.727	Prob > F =	0
Residual	2.29	86	0.027	R-square =	0.69
Total	7.38	93		Adj. R-square =	0.67
				Root MSE =	0.163

Variable*	Coefficient	Std. Error	t	Prob > t	VIF
LN(NO_2)					
(Constant)	8.06E+00	1.177	6.85	0.00	
RD1_200	1.84E-01	0.020	9.04	0.00	1.20
RD2_50	5.56E-01	0.300	1.85	0.07	1.11
IND750	1.63E-03	0.001	3.04	0.00	1.20
DC2000	8.28E-05	0.000	4.66	0.00	1.38
X	-8.01E-06	0.000	-4.31	0.00	1.06
D_WIND1500	1.32E-01	0.040	3.30	0.00	1.20
TRAF500	1.11E-03	0.001	1.96	0.05	1.32

*RD1_200 – measure of expressway within 200m; RD2_50 – measure of major roads within 50m; IND750 – measure of industrial land use within 750m; DC2000 – density of dwellings within 2000m (Kernel estimate); X – UTM NAD83 x-coordinate; D_WIND15 – Boolean identifier whether downwind and within 1500m of nearest expressway at PM-peak traffic; TRAF500 – Density measure of 24 hour traffic counts within 500m.

The scatter plot presented in Figure 3 demonstrates that this model produces reliable predictions with no significant outliers or heteroskedasticity. Examination of Cook's distance and leverage statistics confirmed the absence of significant outliers. Additionally, Moran's *I* tests suggest that spatial autocorrelation is insignificant in this model when using a first-order adjacency matrix.

Cross Validation of Regression Results

Several cross-validation analyses were also undertaken to confirm the predictive capacity and stability of the results. First, the regression model was run with a random selection of only 65 of the records. This action was repeated several times and produced comparable results to those achieved from the full data set in each instance. Each model with only 65 cases produced results that were remarkably similar to the model with all 94 cases.

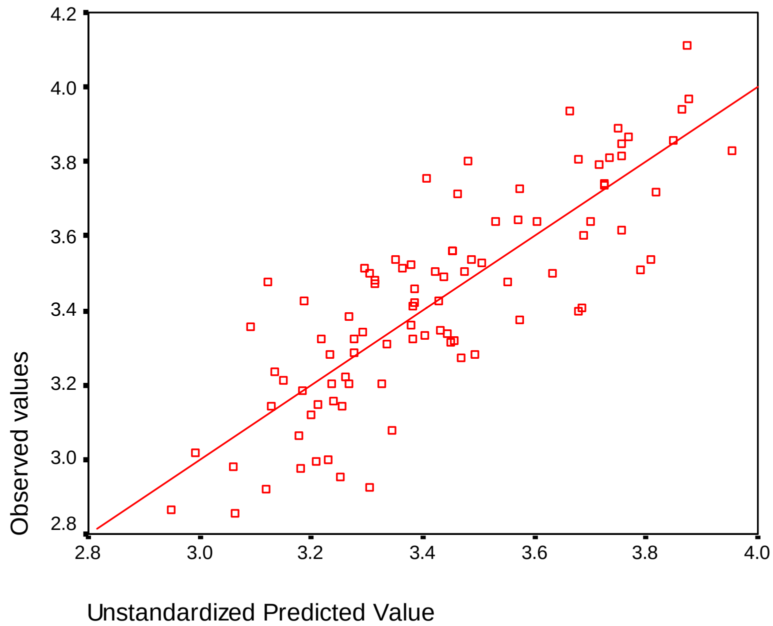

Figure 3: Logarithmic-observed mean NO_2 on predicted value.

Second, the coefficients were used from the model using 65 cases to predict NO_2 concentrations at the 29 excluded sampling locations. The model slightly over predicted for these locations, but the average difference was small in both absolute and relative terms. In each of the cross-validations, the average difference was not greater than 2 parts per billion, translating into an average relative difference of less than 4.0%. The results of this comparison are presented in Appendix 2.

Third, an attempt to compare the modeled results with the data collected by government operated continuous monitoring stations for five co-located sites for the 17-day sampling period was made. Data for only 3 of the 5 co-located sampling locations were available. Using government monitored levels as a reference datum for gauging measurement error by the passive Ogawa samplers, it was possible to conduct groups of impartial validations. First, a validation using longer term averages was also implemented. Five-year (1997-2001) average and the September, 2001, average NO_2 concentrations were available through Environment Canada's National Air Pollution Surveillance Network (NAPS) reports. Second, a temporally matched validation (the two week period in September 2002) using Ontario Ministry of Environment (MOE) data was conducted. The modeled values were also compared to the Ogawa measurements made under this study in September 2002. These results indicated that the differences in monitoring technology and temporal variation produce relatively moderate errors when comparing measured values to modeled values (Table 2). As more temporally matched data are used, the relative error is similar between the land use regression model and the government data decreases (Table 3). Yet, in the ideal case, more government monitoring sites would be necessary to conduct a thorough statistical analysis of the error.

Table 2: Comparison of the land use regression model (LUR) to National Air Pollution Surveillance network (NAPS) and respective Ogawa sampled values.

Station Location	LUR predicted NO_2 ppb (Sept/02)	NAPS Mean NO_2 ppb (1997-2001)	NAPS Mean NO_2 ppb (Sept/01)	Ogawa Mean NO_2 (Sept/02)	% Difference LUR-NAPS (1997-2001)	% Difference LUR-NAPS (Sept/01)	% Difference LUR-Ogawa (Sept/02)
60410	26.9	24.0	21.6	28.2	***12.1***	***24.5***	***-4.6***
60413	25.3	24.3	21.8	20.1	***4.1***	***16.1***	***25.9***
60403	36.9	28.9	26.4	38.0	***27.7***	***39.8***	***-2.9***

Table 3: Comparison of the land use regression model and Ogawa sampled values to temporally matched government monitoring data.

Station Location	LUR predicted NO_2 ppb (Sept/02)	Ogawa Mean NO_2 (Sept/02)	MOE Mean NO_2 ppb (Sept/02)	% Difference LUR-MOE (Sept/02)	% Difference Ogawa-MOE (Sept/02)
60410	26.9	28.2	23.4	***13.0***	***17.0***
60413	25.3	20.1	19.9	***21.3***	***1.0***
60403	36.8	38.0	28.5	***22.6***	***25.0***

Mapping the Model

Kriging analysis was initially used to explore the overall trends present in the sampling data. Figure 4 shows a kriging surface generated with a spherical model of NO_2 across the city using the 95 data points. The downtown area of the city appears to have the highest levels of NO_2. This was also the area of the one monitoring location that was located adjacent to an active construction site. Using this technique it was feasible to visualize possible outliers in the data. Further, the area to the east of the downtown core, along Lake Ontario, appears to have relatively low measures of NO_2.

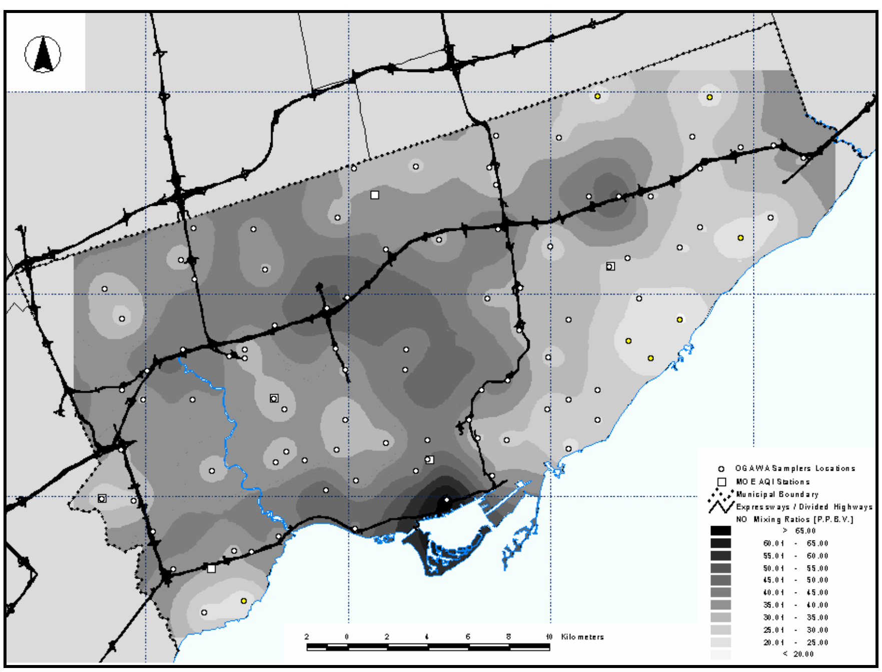

Figure 4: Kriged surface generated with a spherical model of NO_2 across the city using the 95 data points.

After deriving the parsimonious operational model, the coefficients were used to map a predicted pollution surface for exposure assignment in future health studies. Individual raster surfaces were created for each of the seven independent variables included in the model (listed in Table 1), which were then summed together with the Raster Calculator in ArcGIS 8 to generate the overall predicted surface.

The land use regression model created a predictive pollution surface with the expected characteristics (see Figure 5). Specifically, areas in proximity to expressways and in the downtown core appeared to have higher levels of NO_2, while areas with less development in the northeast of the city exhibit lower levels. Although the overall patterns remain similar, this map shows more detailed spatial variation than the kriging map.

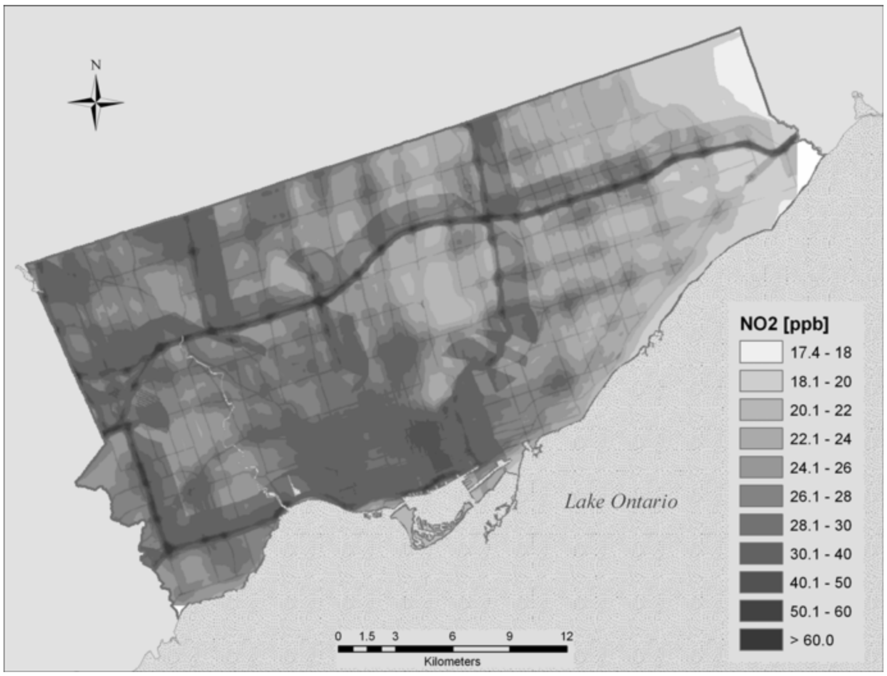

Figure 5: Operational land use regression predicted surface for Toronto.

DISCUSSION AND CONCLUSION

In this paper the determinants of ambient NO_2 throughout the City of Toronto, Canada, have been modeled. The results suggest that a stable predictive surface can be derived for this North American city using the LUR method. The difference in predictability when compared to some European models possibly arises from the variations in land use between European and North American cities. Further cross validation in other North American locations will lend insight on why these differences exist. As mentioned earlier, postwar sprawl in the North American city has five important characteristics that may contribute to the difference between the European and North American results presented here: (1) deconcentrated development (i.e., lower population density than in earlier periods); (2) decentralized, meaning more new development occurs in suburban rather than central areas; (3) homogenous with very little mix in land use types; (4) large scale meaning extensive subdivisions, industrial parks, and commercial centers; and (5) segregated land use types that create a need for travel between residential and commercial (Fowler, 1992; Ewing et al., 2002). Taken together, these characteristics increase the demand for travel by automobiles, and they probably create an exposure surface with more spatial variability than in European urban areas, which seem to have higher but less variable concentrations overall. Predicting a more complex exposure surface may have contributed to the lower R^2 values observed in this study.

In addition, some of the European studies exposed the monitors for longer periods or for multiple seasons. The longer temporal run of monitoring data may have stabilized the monitor readings, contributing to the proportion of explained variance. This paper is reporting the first two-week sampling period in a larger study. After subsequent seasonal sampling is conducted, the data will be pooled together in line with European studies with the expectation that similar predictive capacity will be achieved, as a result of a sample more representative of the overall urban pollution variability.

The sensitivity of the models to variable specification also requires attention in future research. Population density variables, for example, could produce a wide range of results, depending on the scale of the data inputs, the size of the buffer, and the method for operationalizing the variables. Again further empirical work in North America will be required to assess the adequacy of different variable specifications.

This model has been the first LUR to incorporate influence of wind direction on predicted pollution concentration, but much more must be done to include impact of other meteorological variables such as wind speed, temperature, humidity, and atmospheric stability. The way forward for improving the land use regression techniques appears to be the development of some hybrid model that combines the positive features of this method, particularly the local-scale land use information, with more sophisticated emission transport models such as MM5 coupled with emission models such as Mobile 5.

Good agreement was found between the 4 samples at each location (i.e., two double-sided Ogawa monitors). For future seasonal monitoring, only one Ogawa sampler will be used at each location, with 25% of locations containing duplicate Ogawa samplers. These duplicates will assure a means to assess data quality. Although the cross validation produced reasonable results for the same period of deployment with the same monitors, larger differences were found when comparing our predictions to temporally matched and five-year average concentrations from MOE and Environment Canada NAPS sites. The difference between the model predictions and the government monitors is difficult to assess with the limited number of available government stations to conduct cross-validations. Larger variations between Ogawa monitors and the government monitors may have occurred due to the small number of locations available from MOE and Environment Canada for comparison, the difference in monitoring technology, or the temporal variability in emission and meteorological variables. Regardless of the specific reason for this discontinuity in the results, this finding suggests longer monitoring periods covering all seasons may be necessary to capture the intra-urban variability in traffic pollution.

In future research, additional meteorological and point sources emission variables will be incorporated into the model. Additional monitoring will be conducted during different seasons with co-located fine particle monitoring stations to assess the composition and predictability of these pollutants. In a separate study, these NO_2 exposure models have linked to a large cohort of patients from respiratory clinics across Toronto to assess associations at the intra-urban scale to advance previous research using less sophisticated exposure metrics (see Finkelstein et al., 2003 for related studies). Along with other collaborators, similar monitoring networks have also been implemented in other Canadian cities (i.e., Hamilton, Montreal and Vancouver). Pooled estimates from these cities may be used to derive exposure assessments for linkage with the National Population Health Survey. These estimates will in turn allow for assessment of between and within city variation in air pollution exposures and health effects for the Canadian population.

In developing the national-level models, a trade-off inherent in LUR method will become more pronounced: the more the model is refined to specific conditions in one locale, the less transferable and operational it becomes. For example, inclusion of wind direction would require sophisticated meteorological models for each new area. The same could be said of including potential important microenvironmental variables such as street canyons. It would be virtually impossible to document each one of these canyons for extrapolating across many locations within a city, yet alone between them. One solution may arise in the form of remotely sensed data that could be used to assess characteristics such as street canyons, and this would allow for incorporation of these data into the computing environment.

The LUR maps showing predicted surfaces appear to capture small-area variation in NO_2 concentrations more effectively than geostatistical alternatives such as kriging. These small-area variations are probably more important to the exposure experience of subjects in a given health study and, as a result, may detect health effects that would have gone unnoticed with government monitoring data or even kriging estimates. For this reason, the LUR appears worthy of further study in a North American context.

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APPENDIX 1:
BIVARIATE REGRESSION ANALYSIS ON 83 VARIABLES

	Variable	Units	Description	R square	t score
1	Dist_Exp	Km	Distance to nearest RD1	.277	-5.966
2	Basket	Binary	Identifier of samplers located at major 'basket weave' intersections	.045	2.101
3	TruckVol500	Count	Sum of 24hour truck counts on selected RD1s within 500m	.247	4.955
4	HwyFlow1000	Count	Sum of 24hour traffic counts on RD1s within 1000m	.242	5.446
5	RdFlow300_24	Count	Sum of 24hour traffic counts on roads within 300m	.061	2.450
6	RdFlow500_24	Count	Sum of 24hour traffic counts on roads within 500m	.157	4.169
7	AmFlow500	Count	Sum of AM peak traffic counts on roads within 500m	.143	3.935
8	PmFlow500	Count	Sum of PM peak traffic counts on roads within 500m	.137	3.846
9	AmDiv24	%	Am peak counts divided by 24 hour totals (within 500m)	.001	-.335
10	Rd_Density	Ha	Total area of RD1, RD2 and RD3 within 300m	.347	7.032
11	RD1_50	Km	Length of road within 50m	.233	5.315
12	RD2_50	Km		.063	2.494
13	RD3_50	Km		.073	-2.706
14	RD1_50200	Km	Length of road between 50 & 200m (annulus buffer)	.311	6.479
15	RD2_50200	Km		.045	2.086
16	RD3_50200	Km		.115	-3.482
17	RD1_200	Km	Length of road within 200m	.314	6.524
18	RD2_200	Km		.055	2.326
19	RD3_200	Km		.120	-3.569
20	RD1_300	Km	Length of road within 300m	.301	6.325
21	RD2_300	Km		.082	2.885
22	RD3_300	Km		.106	-3.315
23	RD1_300500	Km	Length of road between 300 & 500m (annulus buffer)	.154	4.110
24	RD2_300500	Km		.106	3.326
25	RD3_300500	Km		.047	-2.150
26	RD1_500	Km	Length of road within 500m	.245	5.489
27	RD2_500	Km		.128	3.702
28	RD3_500	Km		.074	-2.727
29	RD1_750	Km	Length of road within 750m	.245	5.487
30	ELEV	m	Elevation at sampling site	.008	-.852
31	X	UTM	Geographic location (east/west)	.114	-3.451
32	Y	UTM	Geographic location (north/south)	.047	-2.146
33	EADens	Count	Enumeration Area population density (polygon thematic map)	.003	-.525
34	EA750	Count	Enumeration Area population density kernel estimate, 750m	.014	1.135
35	EA1000	Count		.022	1.444
36	EA1250	Count		.030	1.707
37	EA1500	Count		.038	1.927
38	EA2000	Count		.045	2.095
39	EAs2000	Count	Simple density estimate	.043	2.053
40	EA2500	Count		.045	2.101
41	CTDens	Count	Census Tract population density (polygon thematic map)	.001	.358
42	CT750	Count	Census Tract population density kernel estimate, 750m	.016	-1.219
43	CT1000	Count		.012	-1.048
44	CT1250	Count		.006	-.773
45	CT1500	Count		.003	-.490
46	CT2000	Count		-.010	.160
47	CTs2000	Count	Simple density estimate	.011	1.014
48	CT2500	Count		-.007	.602
49	PC2500	Count	Postal Code population density kernel estimate, 2500m	.006	.726
50	PC5000	Count		.028	1.638
51	DC1000	Count	Enumeration Area density of dwellings kernel estimate, 1000m	.013	1.104
52	DC2000	Count		.030	1.683
53	DC2500	Count		.030	1.706
54	DC5000	Count		.050	2.221
55	DwVal	Count	Enumeration Area average dwelling value (polygon thematic map)	.003	-.491
56	Dw1000	Count	Enumeration Area average dwelling value, kernel estimate, 1000m	.013	1.098
57	Dw1500	Count		.024	1.523
58	Dw2000	Count		.030	1.682
59	Dw2500	Count		.030	1.697

	Variable	Units	Description	R square	t score
60	Open300	Ha	Area of land use within 300m	.043	2.033
61	Res300	Ha		.058	-2.395
62	Comm300	Ha		.018	-1.288
63	Indust300	Ha		.028	1.628
64	Gov/Inst300	Ha		.000	-.029
65	Open400	Ha	Area of land use within 400m	.029	1.672
66	Res400	Ha		.065	-2.546
67	Comm400	Ha		.012	-1.057
68	Indust400	Ha		.031	1.721
69	Gov/Inst400	Ha		.001	.260
70	Open500	Ha	Area of land use within 500m	.019	1.340
71	Res500	Ha		.069	-2.625
72	Comm500	Ha		.003	-.533
73	Indust500	Ha		.031	1.725
72	Comm500	Ha		.003	-.533
73	Indust500	Ha		.031	1.725
74	Gov/Inst500	Ha		.002	.447
75	Open750	Ha	Area of land use within 750m	.003	.486
76	Res750	Ha		.071	-2.663
77	Com750	Ha		.017	1.275
78	Indust750	Ha		.033	1.781
79	Gov/Inst750	Ha		.009	.927
80	D_WIND	BOOL	Down wind or not	.030	1.689
81	D_WIND5	BOOL	Down wind or not within 500m	.193	4.709
82	D_WIND10	BOOL	Down wind or not within 1000m	.193	4.720
83	D_WIND15	BOOL	Down wind or not within 1500m	.193	4.720
84	TRAF300	Count/km^2	Density estimate of 24 hour traffic count within 300m	.053	2.287
85	TRAF500	Count/km^2	Density estimate of 24 hour traffic count within 500m	.062	2.473

APPENDIX 2:
CROSS-VALIDATION SHOWING ABSOLUTE AND RELATIVE DIFFERENCE BETWEEN OBSERVED AND MODELED VALUES FOR 30 RANDOMLY SELECTED CASES

Cross Validation 1				**Cross Validation 2**				**Cross Validation 3**			
Final Model	**Cross Predicted 1**	**Difference**	**% Difference**	**Final Model**	**Cross Predicted 2**	**Difference**	**% Difference**	**Final Model**	**Cross Predicted 3**	**Difference**	**% Difference**
35.6	34.6	-1.0	-2.8	31.5	29.7	-1.8	-6.2	35.6	36.8	1.2	3.3
41.1	42.1	1.0	2.5	25.3	25.0	-0.3	-1.4	41.1	42.1	1.1	2.5
41.8	38.1	-3.7	-9.7	48.1	47.3	-0.8	-1.6	41.8	41.7	-0.1	-0.3
30.1	31.0	0.9	2.7	29.3	29.8	0.5	1.5	30.1	31.4	1.3	4.1
32.7	36.4	3.7	10.1	31.7	30.1	-1.5	-5.1	32.7	35.1	2.4	6.8
39.9	45.6	5.6	12.3	22.7	23.1	0.4	1.8	39.9	41.7	1.7	4.1
25.5	25.0	-0.6	-2.3	42.7	44.6	1.8	4.1	25.5	25.5	0.0	0.0
29.5	29.5	0.1	0.2	19.9	20.2	0.3	1.6	29.5	29.4	-0.1	-0.4
31.1	31.5	0.5	1.4	28.5	28.2	-0.3	-1.1	31.1	29.9	-1.2	-4.0
45.0	59.0	14.0	23.7	39.6	39.1	-0.6	-1.4	45.0	53.8	8.8	16.3
41.4	48.3	6.9	14.3	21.4	22.1	0.7	3.3	41.4	45.0	3.6	8.0
25.9	25.6	-0.3	-1.1	34.1	34.0	-0.1	-0.2	25.9	25.4	-0.5	-1.8
27.2	27.9	0.6	2.3	28.3	29.0	0.6	2.2	27.2	27.1	-0.1	-0.4
45.5	52.3	6.8	13.0	24.5	24.7	0.1	0.5	45.5	50.4	4.9	9.7
46.9	52.9	6.0	11.4	30.6	31.1	0.5	1.5	46.9	51.5	4.6	9.0
25.9	26.9	1.0	3.7	27.8	27.8	-0.1	-0.2	27.8	28.0	0.2	0.6
26.2	25.6	-0.7	-2.6	32.3	30.7	-1.6	-5.2	32.3	32.4	0.1	0.2
52.0	53.6	1.6	3.0	24.2	23.9	-0.4	-1.6	24.2	24.2	0.0	-0.1
47.7	49.6	2.0	4.0	25.0	24.7	-0.2	-0.9	25.0	25.3	0.3	1.4
26.2	25.6	-0.6	-2.3	34.8	33.7	-1.1	-3.3	34.8	36.2	1.3	3.6
42.8	43.8	1.0	2.3	29.4	29.8	0.4	1.4	29.4	29.6	0.2	0.6
33.3	33.6	0.3	0.8	44.3	46.3	2.1	4.4	44.3	46.5	2.2	4.7
39.9	39.7	-0.2	-0.5	21.3	22.0	0.7	3.4	21.3	21.5	0.2	1.2
24.1	23.9	-0.2	-0.8	39.0	38.1	-0.9	-2.2	39.0	41.7	2.7	6.4
25.4	27.9	2.5	8.8	24.0	24.3	0.3	1.4	24.0	25.6	1.6	6.4
31.9	32.0	0.1	0.3	40.4	41.7	1.3	3.0	40.4	42.9	2.5	5.8
35.6	35.5	-0.1	-0.4	22.6	22.9	0.3	1.3	22.6	22.7	0.1	0.4
26.9	29.4	2.5	8.5	27.5	27.4	-0.1	-0.2	27.5	27.5	0.1	0.3
31.3	36.0	4.7	13.0	32.1	32.6	0.5	1.4	32.1	32.7	0.6	1.9
	Average =	**1.9**	**4.0**		**Average =**	**0.0**	**0.1**		**Average=**	**1.4**	**3.1**