Geographies of Susceptibility and Exposure in the City: Environmental Inequity of Traffic-Related Air Pollution in Toronto

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Introduction

The scope of environmental justice research has widened considerably in recent years to reflect not only inequities in environmental health exposures but also interest in health effects and a greater range of hazards. Underpinning these developments – and the focus of this paper – are prescriptions for and critiques of the methods used in environmental justice research and the substantive conclusions that follow (Brulle and Pellow 2006; Downey 2006; Mohai and Saha 2006; Bowen 2002). A principal concern is that high-quality environmental monitoring data are rarely available or publicly accessible. Using data from a large air pollution sampling campaign in Toronto, we analyze the geographies of susceptibility and exposure to traffic-related air pollution, namely nitrogen dioxide (NO_2), within and across neighbourhoods.

Traffic emissions are now the single largest source of air pollution in the typical North American city (Molina and Molina 2004). Perhaps more than any

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other city in Canada, traffic emissions in Toronto reflect a much more heterogeneous spatial distribution because the City has an extensive network of major roads, highways and expressways. Recent studies from the nearby City of Hamilton have suggested that proximity to roadways may advance mortality rates by up to 2.5 years in the general population and is associated with an increase in cardiopulmonary death of over 20% (Finkelstein et al 2003).

If Toronto traffic emissions are spatially heterogeneous so too is its social geography. The region both represents the social disparities and spatial segregation of large Canadian metropolises. It has some of the most extreme cases of intra-urban wealth and despair gradients. However, contrary patterns also exists with some new immigrants stratified by status and type (e.g. refugees) veering away from traditional central-city settlement patterns via direct suburban settlement (Hiebert 2000). Using high-resolution pollution data, our question is whether and to what extent social geography and NO_2 systematically map onto one another in Toronto. We begin with an overview of each of these issues and then turn to the data and methods used to bring the urban physical and social environments together. We conclude with a discussion of the broad transportation and socioeconomic trends that improve understanding of environmental justice in the increasingly variegated landscape of the North American city.

Background: Methodological Concerns

Now into its third decade, environmental justice research grew out of early influential studies (e.g. US GAO 1982; Bullard 1990) that led to both distributional research on inequities of exposures to health hazards and process research on the socio-political mechanisms that generate such inequities (Cutter 1995). In the former camp the noted UCC (1987) *Commission on Racial Justice* found that in the United States people of colour were twice as likely as Whites to live in a community with a commercial hazardous waste facility and three times as likely to have multiple facilities. The political power of these civil rights statements meant that research strategies developed around revealing the presence and degree of disproportionate co-location of such facilities and poor and visible minority communities (e.g. Glickman 1994).

Much of the literature on methodology in the last decade revolves around the simple assumption that underlies co-location studies; in terms of the spatial extent of hazards; the modifiable areal units of administrative boundaries and related ecological fallacy; the toxicity and assignment of exposures; and the relationship to health outcomes. Researchers have redressed some of these shortcomings with new conceptual frameworks (O'Neill et al 2003; Morello-Frosh 2006), studies of health effects (Rogers and Dunlop 2006; Finkelstein et al 2005; Wheeler and Ben-Shlomo 2005) and new exposure assessment/analytic methods (e.g. McConnell et al 2006; Mohai and Saha 2006; Mennis and Jordan 2005; Harner et al 2002). Still, reliable exposure assessment remains a difficulty because of the lack of high quality environmental monitoring data and case studies still (sometimes must) rely on proximity (distance decay) methods to assign exposures (e.g. Houston et al

2006; Jacobson et al 2005). This is especially true where hazards are generated diffusely across geographic space (Lejano and Smith 2006).

Transportation has become one of the largest source of criteria (health hazardous) pollutants with links to health effects, especially in large city-regions, and the relative contribution of emissions from traffic has increased compared to point sources which have tended to decline over the past two decades (Colvile et al 2001; Molina and Molina 2004). Although spatially diffuse throughout the urban area, significant variability occurs at localised (within hundreds of metres) spatial scales (Brauer et al 2003). Some environmental justice researchers have studied the inequities of transportation systems using a variety of approaches. For example, Green et al (2004) examine the proximity of California schools and major roadways, finding that the highest traffic counts (vehicles per day) on nearby roadways (within 150 metre buffer) were associated with economically disadvantaged and non-white populations. Apelberg et al (2005) analysed associations between the EPA's National Air Toxics Assessment (NATA) and census tract socioeconomic data in Maryland and found that cancer risk was greatest for road-source emissions and low-income and racial minority areas. Similarly, studies in southern California (Morello-Frosch et al 2001; Pastor et al 2005) have used emissions inventories (including NATA) to assess the health impacts of a range of sources, reporting mobile/transportation sources as most important for lifetime cancer risk, but especially for racial minorities. These results, they argue, point to the need for land use and public policy development on transportation emissions to reach beyond obvious large-facility emissions.

Not surprisingly environmental justice research focusing on transportation has attracted its own methodological rejoinders and prescriptions (Mills and Neuhauser 2000; Jacobson et al 2005). For example, Most et al (2004) addresses the difficulty of population assignment for devising comparison groups and assigning exposure to transportation externalities (noise in their study). They demonstrate that alternative spatial scales can significantly alter study results. As the weight of evidence grows, concerns about the scientific validity of the findings remain, with particular emphasis on accuracy of exposure assignment at the local scale. This paper seeks to assess environmental inequity using direct measurements of small area variation in traffic pollution with a rich array of socioeconomic data on Toronto, Canada.

Improving Exposure Assessment in Toronto

When Ott (1995) proclaimed the 'new science of exposure analysis' he anticipated a series of studies that would develop, among other things, air pollution exposure assessment at fine spatial scales. Symbolically these developments emerged as the previous dominant mode of air pollution health research – time-series and cohorts studies (based on limited inter-urban monitoring) – were aptly summarised in the Health Effects Institute's (Krewski et al 2000) *Reanalysis Project*. Just prior to the *Reanalysis Project*, and at an increasing pace since, exposure analysts have turned their attention to intra-urban or within-city analyses. As part of a larger multi-site project concerned with the chronic health impacts of air pollution (e.g. Sahsuvaroglu et al 2006; Kanaroglou et al 2005), this study of Toronto provides an opportunity to generate hypotheses on the microgeographies of ambient air pollution susceptibility and exposure.

Briggs et al (1999) and Hoek et al (2001) were among the first to use localised (typically under one kilometre) land use composition around monitoring sites to derive parameters for air pollution estimation at unsampled locations. Brauer et al (2003) used a similar approach to assign exposures of traffic-generated long-term ambient particulate concentrations to members of three birth cohorts in The Netherlands, Munich and Stockholm in order to assess asthma incidence. They show that 50% to as high as 81% of the spatial variability (from a special sampling campaign) of ambient concentration could be captured by a parsimonious regression model of land use covariates including traffic-related variables. More recently Gilbert et al (2005) report a multivariate land-use regression (LUR) model predicting 54% of the spatial variability of NO_2 in Montreal based largely on traffic variables such as distance from the nearest highway, traffic counts on the nearest highway and length of highways and major roads within 100 metres of a sampling location. They argue that the robustness of such land use regression models can be used to reduce exposure misclassification in epidemiologic studies – a key point since more accurate exposure assignment will improve health effects models and in particular that health impacts are muted when exposure assignment is weak (Molitor et al 2006).

Environmental justice researchers have also shown concern over the linkage between transportation systems, health, health care and social costs (e.g. Chakraborty et al 1999). Toronto has a history of grassroots movements aimed at transportation issues, most famously the halting of the Spadina Expressway's construction near the central city in the 1970s (Caulfield 1994). At the same time the region is home to one of the widest expressway corridors anywhere in North America, highway 401, which carries over 400,000 vehicles per day on average, and there are no empirical data on whether these variegated exposures link to SES.

Equally prominent is Toronto's complex social geography. Social polarisation in general has risen in Canadian cities in recent years, especially in the largest centres (MacLachlan and Sawada 1997; Bourne 1997). As these trends continue to unravel across the urban landscape it is unclear whether inter- and intra-urban polarisation and deprivation can be attributed to economic restructuring, urban growth and regional effects (Broadway and Jesty 1998; Langlois and Kitchen 2001). Whatever the explanation, economic/class spatial segregation is on the rise across the Canadian urban system and Toronto's experience is typical if slightly worse than average (Ross et al 2004). Walks (2001) demonstrates in empirical detail that economic and occupational restructuring are associated with increasing income inequality and social polarisation in Toronto, including well-established spatial processes of gentrification/social upgrading in selected central-city locations. At the same time complexity is the story of the evolving social ecology of Toronto, including new immigrant settlement trends diversified by status and type (e.g. refugees) with direct suburban settlement, for example, emerging as a dominant pattern (Hiebert 2000).

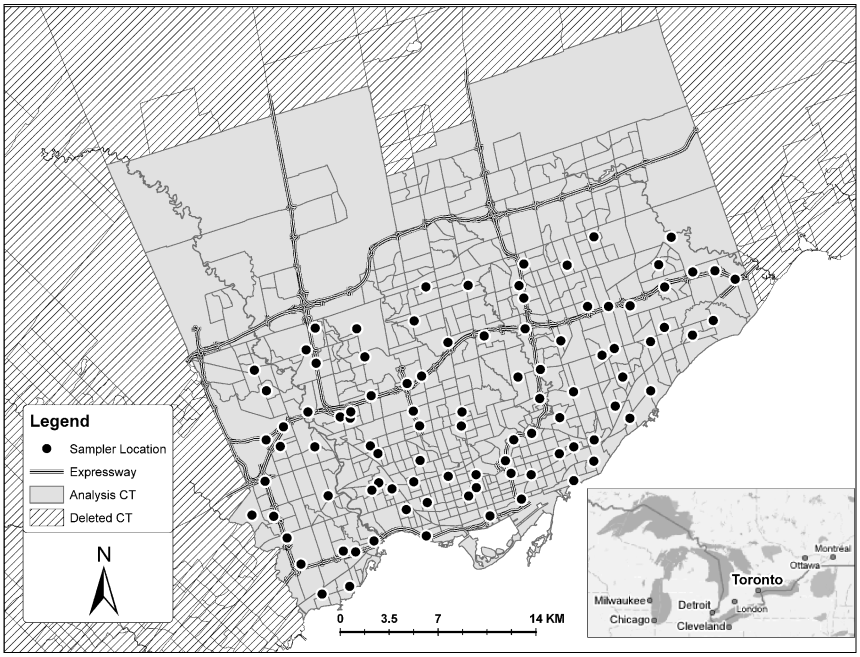

FIGURE 1 Air Pollution Sampling Locations and Study Neighbourhoods

How might transportation emissions and this complex social geography intersect to produce geographies of susceptibility and exposure? Finklestein et al (2005) have shown in nearby Hamilton that ambient particulate is inversely correlated with 2001 neighbourhood income, and that particulate matter relates to elevated cardiovascular mortality. The latter study moves substantially beyond the exposure errors associated with sparse monitoring networks. The correlation with neighbourhood income suggests potential socioeconomic patterning of ambient air pollution at the intra-urban scale.

Methods

The study is situated in the City of Toronto on the Northern Shore Lake Ontario (Figure 1). Toronto is Canada's largest city with a metropolitan population of just over 5 million in 2001. Many major highways and larger arterial roads traverse Toronto, leading to a wide range of variation in traffic and related pollution. The expansive network of highways and the demonstrated health effects in nearby locations make Toronto an excellent location in which to examine inequities of exposure to traffic-related air pollutants.

A geographic information system (ArcGIS 9.1 ESRI, Redlands, CA) was used to incorporate the neighbourhood socioeconomic and air pollution values for the analysis. Neighbourhood (census tract) socioeconomic data are drawn from Statis-

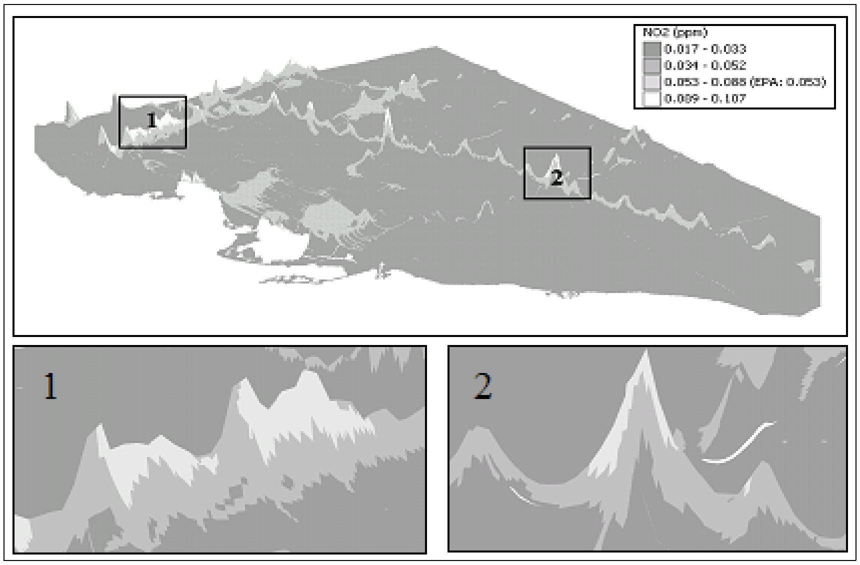

FIGURE 2 Estimated/Validated Neighbourhood NO2 Values
Note: The surface is rendered with 60x exaggeration to make ambient concentrations visible.

tics Canada's 2001 census. These data include a range of neighbourhood markers used in past studies of environmental justice in Canadian cities including dwelling values, household income, family status, immigrant/visible minority status and occupational markers. The overriding hypothesis, following the basic premise of environmental justice research, is that lower SES neighbourhoods carry the greatest burden of chronic exposure to traffic-generated NO_2.

NO_2 estimates are derived from a land use regression (LUR) of a special NO_2 sampling campaign in Toronto for two weeks in September 2002. Using a location-allocation algorithm (Kanaroglou et al 2005), ninety-five samplers (duplicate passive two-side Ogawa samplers) were sited throughout the region to capture both the greatest population exposure and spatial variability of NO_2. Sampled values were then modelled as a function of local land use and transportation variables (Jerrett et al 2007). Specifically, land use regression seeks to use the observed pollution readings as the dependent variable and the adjacent land use and transportation data as predictors. The final regression model yielded a coefficient of determination (*R-square*) of 0.69 including variables for 24-hour traffic counts and road measures, industrial land use and dwellings within 2000 m of the monitoring location. Final estimates were enhanced by applying wind fields to ambient NO_2 distribution so that sampling locations up to 1500 m downwind of major highways are assigned elevated NO_2 levels. The exposure surface is illustrated in Figure 2. As shown, the model produces fine scale variation, with the highest concentrations in the downtown core areas of the City and around the intersection of major highways. The lowest levels are observed in the northeast of the City.

Ambient NO_2 values were then assigned to neighbourhoods in two steps. First

LUR model coefficients were used to estimate NO_2 values for each 5m cell in a raster surface spanning most of the City of Toronto. Second, a grid-on-point overlay procedure was used to assign NO_2 values from this raster surface to spatially weighted (by residential land use) centroids in each neighbourhood. The product of these estimates and procedures is a geodatabase of 606 neighbourhood-level air pollution and socioeconomic markers on income, employment, dwelling values, family status, immigrant and visible minority status and reliance on social transfers.

An environmental justice analysis of this geodatabase is based on disentangling the neighbourhood socioeconomic markers that associate with ambient NO_2. As in prior research ordinary least squares models based on manual forward selection are used to establish the nature and strength of relationships. Standard model diagnostics are used to assess all models and spatial analysis of residuals is also undertaken. The picture that emerges from the analysis is complex with many significant variables. Accordingly further steps were taken to augment the analysis. First, the analysis was refined with sensitivity tests by removing outlier cases. Second the NO_2 data were simplified with a binary division of high versus low exposures (at the median of the natural logarithm of NO_2) in a logistic regression approach in order to capture the neighbourhood markers that discriminate high and low exposures. Finally, to address the spatial dependence of the residuals in the OLS models a spatial linear regression model is estimated.

Model Results

Table 1 shows descriptive statistics of the NO_2 and neighbourhood socioeconomic data used in the analysis. Figure 2 shows the US EPA's 24 hour exceedance objective of 53 ppb. While this is not directly comparable to the two week averages produced here we can see how some areas can range far above acceptable standards. The first important feature is that annual average ambient NO_2 values range by 33.5 ppb across neighbourhoods. Urban background levels were very similar though the spatially refined sampling and modelling used here reveals a neighbourhood maximum of 51.2 ppb, 65% higher than the maximum of the government monitoring stations (Pengelly 2001).

Table 1 also shows neighbourhood socioeconomic descriptive statistics of Toronto's variegated social geography. All variables show marked disparities between neighbourhoods of affluence and despair. High status neighbourhoods, for example, can be almost entirely white, have median household incomes above $200,000, almost no lone-parent families or nearly no adults with less than grade nine education. By contrast, low status neighbourhoods can be entirely visible minority, have one-fourteenth the median household income, one-half of families led by lone-parents and 40 percent of adults with low education. In short Toronto is a city of marked neighbourhood air pollution and socioeconomic contrasts.

The OLS models reveal a subtle geography of susceptibility and exposure. Model 1 in Table 2 predicts 30% of the spatial variability of NO_2 with all but two variables taking the expected sign. Median household income and high status

TABLE 1 Variable Definitions and Descriptive Statistics

	Mean	Standard Deviation	Minimum	Maximum	Range
Census tract NO2, Y_1	27.5	4.9	17.7	51.2	33.5
Dwelling value, X_1	281197	131487	91845	1418890	1327045
% Low income families, $X_{2(a)}$	18.0	10.8	1.8	72.8	71.0
% Low income individuals, $X_{2(b)}$	38.0	14.4	5.3	83.3	78.0
% Low education, X_3	10.9	7.7	0.3	41.2	40.9
Med. income, X_4	57450	23083	15357	216361	201004
Unemployment rate, X_5	6.7	2.6	1.0	21.3	20.3
% Manufacturing employment, X_6	8.2	6.2	0.3	37.6	37.3
% Lone parent families, X_7	18.4	7.2	3.2	49.6	46.4
% Government transfer payments, X_8	10.8	5.0	1.0	35.1	34.1
% Immigrants, X_9	48.2	14.1	11.4	80.3	68.9
% Visible minorities, X_{10}	40.2	23.6	3.0	97.5	94.5
% High status occupation, X_{11}	36.1	15.5	6.9	77.4	70.5

Note: 1. Y1, estimated annual average N02, ppm; X1, average dwelling value; X2(a), percentage of economic families or unattached individuals over 15 years of age below Statistics Canada's low income cut-off; X2(b), percentage of individuals over 15 years of age below Statistics Canada's low income cut-off; X3, percentage of population 15 years of age or older that has less than grade nine education; X4, median household income; X5, uneployment rate of population 15 years of age or older; X6, percent of the population employed in the manufacturing sector; X7, lone-parent families as a proportion of all families; X8, proportion of total income for the population 15 years of age or older derived from government transfer payments; X9, percentage of population that is of immigrant status; X10, percentage of population that is of visible minority status; X11, percentage of population employed in high-status occupations.[2]

2. *Occupational subcategories A0, A1, A2, A3, A4, B0, B1, B3, B4, C0, D0, E0, E1, F0, G0 from categories A-G in the census, respectively: (A) Managers; (B)Business, finance and administration; (C) Natural and applied sciences; (D) Health occupations; (E) Social sciences; (F) Art, culture and recreation; (G)Sales and service.

3. All independent variables derived from Statistics Canda's 2001 census.

occupation are most significant, followed by education. Low income and lone-parent families are significant but capture less variability. By contrast dwelling values and visible minorities took unexpected signs. We would expect race to increase exposure, although perhaps Toronto's role as a gateway city and destination of a variety of immigrants, including business entrants and the majority of refugee claimants in recent decades, has created a more textured racial landscape. This may also help explain why the visible minority variable is weakest of all. In fact the visible minority and low income family variables are collinear and a simpler model is not sensitive to removal of both (Model 2). Removal of outliers (residuals above 3 standard deviations of the mean; Model 3) produces the same substantive results as Model 1, including counter-intuitive results for visible minorities and dwelling values, though model fit improves. The residuals of Model 3 were tested for spatial autocorrelation using global Moran's *I* test. The results

TABLE 2: OLS and Logistic Regression Models

	Dwelling value, X_1	Low income families, X_2	Low education, X_3	Med. income, X_4	Lone parents, X_7	Race, X_{10}	High status occupation, X_{11}	Model fit: adj. *R sq.*
MODEL								
Model 1[1]	1.744E-07	0.001	0.006	-4.02E-06	0.003	-0.001	0.006	0.30
(OLS, n=569)	(2.2)	(2.3)	(6.2)	(-8.9)	(3.0)	(-2.0)	(8.3)	
Model 2[1]	1.86E-07	--	0.007	-4.22E-06	.004	--	.007	0.29
(OLS with race, income removed, n=581)	(2.4)	--	(6.9)	(-9.5)	(3.4)	--	(9.5)	--
Model 3[1]	1.98E-07	--	0.007	-4.27E-07	0.004	-0.001	0.006	0.33
(OLS with outliers removed, n=564)	(2.6)	--	(6.8)	(-10.1)	(3.6)	(-2.1)	(8.6)	--
Model 4[2]	3.11E-06	--	0.11	-6.03E-05	0.05	--	0.08	8.474 (0.39); 0.32[3]
(Log-odds, n=581)	(4.9, p=0.03)	--	(41.5, p<0.01)	(59.1, p<0.01)	(6.9, p=0.01)	--	(47.6, p<0.01)	--

Note: 1. OLS coefficients, t-values in parentheses.
2. Log-odds model coefficients (change in -2LL if variable removed).
3. Hosmer-Lemeshow chi-square (sig.); Nagelkerke's R-square.
4. See Table 1 for variable definitions.

show that, owing to the local spatial dependence of NO_2 values across the urban field and the relatively low predictive power of the model, there is some spatial clustering (Moran's $I = 0.25$, $p < 0.01$) in the results. [1]

In the above models neighbourhood socioeconomic markers capture about 30% of the spatial variability of NO_2 though they also return a large number of substantive predictor variables. Spatial dependence may also be a problem in substantively interpreting the relationships. To address these issues we employed two further strategies: First, to simplify this picture we employed binary logistic regression by separating 'high' and 'low' exposure neighbourhoods, respectively those above and below median NO_2 (natural log). This allows us to estimate whether the probability of high exposure is associated with markers of neighbourhood disadvantage. The logistic regression shown in Model 4 (Table 2) produces predicted NO_2 logistic scores that are not significantly different from observed values (X_2=8.474, p=0.39) and the model correctly classifies 71% of neighbourhoods as either high or low exposure.

Substantively, the likelihood ratio (-2LL = 646.504) of Model 4 is significantly different than a constant-only model (X_2=158.175, p<0.01) suggesting significant improvement in the fit for the final set of predictors. In terms of indi-

1. Based on a queen's case spatial weights matrix using a distance thresold of five times the mean distance between all census tracts in the analysis of Model 3 (4050 metres). It should be noted that while Moran's *I* shows some positive spatial clustering this test has not adjusted for *k* parametres in Model 3 and therefore likely over-estimates the degree of clustering in the residuals (see Bailey and Gatrell 1995: 269-282). A spatial linear regression model is run to address this autocorrelation in Model 3.

vidual parameters, median income, high-status occupation, low education, dwelling value and lone-parents significantly predict the probability of high NO_2 ; dwelling value slightly less so (p=0.03). As percentage variables, high-status occupation (OR=1.08, 95% CI: 1.06-1.11), low education (OR=1.11, 95% CI: 1.08-1.15) and lone-parents (OR=1.05, 95% CI: 1.01-1.10) produce higher odds ratios, education being the most important. A 1% rise in neighbourhood low education raises the odds of 'high' NO_2 exposure by 10%. The odds ratios of dwelling value and median household income are small but if we truncate these variables by \$10,000 we can interpret their effects more intuitively. Dwelling value (OR=1.03, 95% CI: 1.003-1.06) remains relatively unimportant though the odds of median income (OR=0.55, 95% CI: 0.46-0.65) is large. With a \$10,000 rise in neighbourhood median income we see a reduction in the odds of high NO_2 exposure of 5.5%. In general the logistic regression provides a somewhat clearer picture of important neighbourhood SES markers by removing the low income and race variables and highlighting the protective role of median income. However dwelling value and high status occupation still take the unexpected sign, a point to which we return below.

The second strategy, aimed at addressing spatial dependence in the OLS models, was to use a spatial linear regression (spatial autoregressive, SAR) estimation of NO_2. The model is calculated based on a centroid-to-centroid distance of 4050m to define the connectivity matrix as in the above Moran's I analysis of Model 3 residuals. All calculations were done with S-Plus using the ArcView linkage. Variables were entered via manual backward selection where variables with p values greater than 0.1 were removed until the final selection of variables remained significant at the 0.05 confidence level. Initial estimation excluded the dwelling value variable since it was highly collinear with income and removal of the latter resulted in high collinearity in the final estimated model (condition index > 40). Also, income is the more significant variables in all models. The final SAR model includes: low income families (b = 0.042, p < 0.01), median household income (b = -0.059, p < 0.01; note that the original income variable is divided by 1000 in this case to make the coefficient larger for presentation), manufacturing employment (b = 0.123, p < 0.01) and high status occupations (b = 0.062, p < 0.01). Collinearity between the two employment variables exists but both are necessary to reduce the spatial autocorrelation to an acceptable range. Autocorrelation is still significant (Moran's I = 0.05, p = 8.405e-8) although much smaller than the 0.25 for the residuals of OLS model 3 stated earlier. There are a few differences between the SAR model and those reported in Table 2. First is the presence of the manufacturing variable indicating that neighbourhoods with more residents employed in this sector (indirectly a proxy for low SES) are also more exposed to NO_2. The other variables take the same sign as in the reported OLS and logistic regressions underscoring their substantive relationship with traffic-generated air pollution.

Conclusions and Discussion

Substantively the models of neighbourhood susceptibility and exposure paint a complex picture. In general neighbourhoods marked by low education, lone parent families and low median income were more likely to have higher NO_2 exposure as we would expect. Unexpectedly, visible minorities were sometimes negatively associated with exposure though this variable was less robust. Most surprising is that neighbourhoods marked by high status occupations and high dwelling values were also susceptible to exposures. Referring to Figure 2 what these results point to, certainly in part, is the generally higher ambient NO_2 values in south-western and central-Toronto neighbourhoods where dwelling values tend to be higher and where, therefore, those with higher status occupations are more likely to reside. The high-status occupation variable is one of the most consistent and significant of all tested including in the SAR model. Gentrification may play a role particularly as central-city neighbourhoods in Toronto, as elsewhere, have seen more steeply rising rent gradients since the 1970s (Skaburskis 2006). Indeed the presence of visible minorities may go hand-in-hand with this process as some have argued that ethnic packaging plays a role in changing these gradients, including in Toronto (Hackworth and Rekers 2005). For this set of variables, then, we see some evidence of contrarian results to what might be expected in environmental justice research. In general, the analysis points to inequitable NO_2 exposures with the median income and low education variables bearing most of the association in the models.

Future research can refine this analysis in a number of ways. From the point of view of exposure analysis a larger number of criterion pollutants (such as volatile organic compounds) from similar sampling campaigns already underway may be used to refine the exposure picture and examine health outcomes such as cancer prevalence. If the census tract numbers are sufficient a disaggregation of minority groups may point to alternative experiences based on settlement patterns. Finally with ongoing sampling campaigns a temporal perspective may be built into future work to move beyond a cross-sectional picture.

In the meantime the results of the present study alert us to two policy implications. The first and more direct is that regulatory air pollution monitoring likely significantly under-estimates the range and spatial heterogeneity of ambient NO_2 and air pollution generally. Published reports based on sparse regulatory monitoring represent a rather more limited quantity and range of ambient pollution with obvious implications for health: the impacts on human health are also likely underestimated or, at best, the relationship is fuzzied by exposure misclassification.

The second and more subtle policy implication flows from is that the environmental justice picture may be at once more pervasive and subtle than expected such that the burden of illness is not always socio-spatially inequitable. Following Anderton et al's (1994) early critique of environmental justice research, we have recently seen many contrarian case studies and calls for alternative approaches (e.g. Brulle and Pellow 2006; Downey 2006; Ringquist 2005). As in the present study, new methodologies and emergent health hazards may reveal unforeseen relationships, perhaps especially so in the urban context of dense spatial externalities among land uses and activities. As O'Neill et al (2003) argue it may be that traffic emissions are so spatially diffuse and complex that they make equity analyses more difficult, especially as gentrification and downtown rejuvenation continue to bring greater populations into automobile-dense areas. On the other side of the coin are socio-spatial patterns and trends such as the constantly unfolding picture of residential segregation (e.g. Morello-Frosch and Jesdale 2006) which may further blur the expected picture on the standard variables such as dwelling value. Moreover these contrarian and "more equitable" relationships between socioeconomic status and air pollution suggest new avenues and challenges for environmental justice, health and more broadly urban quality of life (e.g. Heynen et al 2006). What this means for future research is that each case study must be interpreted with place-sensitivity and, at the same time, case studies serve to constantly challenge prevailing wisdom of environmental health and equity relationships.

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