GeoJournal (2010) 75:595–608
DOI 10.1007/s10708-009-9269-6

Transboundary air pollution and environmental justice: Vancouver and Seattle compared

Jason G. Su · Timothy Larson · Timothy Gould · Martin Cohen · Michael Buzzelli

Published online: 6 March 2009

Abstract This paper comparatively analyzes the association between urban neighborhood socioeconomic markers and ambient air pollution in Vancouver and Seattle, the two largest urban regions in the Georgia Basin-Puget Sound (GB-PS) international airshed. Given their similarities and common airshed, Vancouver and Seattle are useful comparators addressing not only whether socioeconomic gradients exist in urban environmental quality but also identifying clues to differences in these gradients between Canadian and American cities. Large air quality sampling campaigns and pollution regression mapping provide the pollution data, in this case nitrogen dioxide—a marker of traffic emissions considered the most important air pollutant for human health in the typical North American city. Pollution data are combined with neighborhood census data for regression and spatial analyses. Median household income is the most consistent correlate of air pollution in both cities, including their most polluted neighborhoods, although neighborhoods marked by immigrant populations do not correlate with high pollution levels in Vancouver as they do in Seattle.

Keywords Transboundary · Environmental justice · Land use regression · Spatial dependency · Lagrange multiplier · Generalized additive model

J. G. Su
Environmental Health Sciences, School of Public Health, University of California, Berkeley, USA

T. Larson · T. Gould · M. Cohen
University of Washington, Seattle, WA, USA

M. Buzzelli (✉)
Department of Geography, Social Science Centre, University of Western Ontario, 1151 Richmond Street, N6A 5C2 London, ON, Canada
e-mail: michael.buzzelli@uwo.ca

Background

Twenty years ago the publication of landmark studies (U.S. General Accounting Office (GAO) 1982; United Church of Christ Commission for Racial Justice (UCCCRJ) 1987; Bullard 1990) founded research in what has come to be known as environmental justice. Spurred by civil and minority rights movements that began in the 1960s in the United States, communities have mobilized to protect their homes and neighbourhoods from the inimical (perceived or real) effects of environmental health hazards such as waste incinerators and noxious landfills. Mobilization is inherently tied to sense of place and is expressed as territorial defense within environmental justice as communities who face threats to the quality of their environments and their health organize and act in response.

Reflecting and reinforcing this movement, research on environmental justice continues to document and analyze the societal distribution of environmental hazards such as air pollution and residential proximity to hazardous waste facilities (Helfand and Peyton 1999; Gee 2004). Disadvantaged communities are defined by common markers of social disparities including income (Evans and Kantrowitz 2002), ethnicity and race (Bhat 2005; Green et al. 2004; Morello-Frosch and Jesdale 2006; Apelberg et al. 2005; Mirabelli et al. 2006), employment (Cummins et al. 2005), education (Buzzelli et al. 2006) and family status (Buzzelli et al. 2003). Studies of environmental justice are inherently spatial in nature (Sheppard et al. 1999) requiring the selection of an appropriate spatial methodology for analyzing the relationship between population and environmental characteristics. Studies have been done at various scales including city-to-city comparisons (Brown et al. 2003), ZIP code (Krieg 2005), census tract (Apelberg et al. 2005; Buzzelli and Jerrett 2004; Morello-Frosch and Jesdale 2006), census block group (Derezinski et al. 2003) and census block (Neumann et al. 1998). Some studies explicitly compare alternative spatial scales (Dolinoy and Miranda 2004). Among them, census tracts (CT) or wards are the most typical spatial unit of analysis. Recent research suggests that CTs may be acceptable approximations of actual neighborhoods for social context (Lee 1999; Overman 2002; Ross et al. 2004; Sampson et al. 1997).[1]

Recent studies show that regression mapping, or land use regression (LUR)—the methodology used here—based on roadway and land use data inputs can be used effectively to predict traffic related pollution concentrations (Brauer et al. 2003; Briggs et al. 1997; Henderson et al. 2007; Jerrett et al. 2005a; Ross et al. 2006; Su et al. 2008). In general LUR has two broad stages: first preliminary input data are used to parameterize a regression model; second, this regression model is used to predict ambient pollution concentrations continuously across geographic space based on localized land uses. The methodology centers on the selection of appropriate buffer sizes around pollution receptor locations in order to identify the relevant quantities and mixes of land uses and activities that contribute to local pollution concentrations. For example Jerrett et al. (2004, 2005b) identified the effectiveness of LUR and buffering for assessments of mortality from traffic-related air pollution for Toronto, Canada, and fine particulate ($PM_{2.5}$) pollution for Los Angles, USA. However because of the uncertainty in identifying optimal buffer sizes, researchers usually select a limited number of buffers and may make ad hoc selections based on presumed highest correlations. We argue that this method might not reflect the best buffer selection by not optimizing the selection of relevant land uses and, as a result, may propogate that process in generating estimates across the entire urban field. While adopting LUR as a general approach in this comparative study, we also seek to advance the method.

As part of the Canada–United States Border Air Quality Strategy (BAQS) that aims to address health issues related to air pollution in GB-PS, the present study draws on prior data collection campaigns to build a novel comparative urban environmental justice analysis. The Greater Vancouver Regional District (GVRD, hereafter Vancouver) and the Seattle Metropolitan Statistical Area (SMSA, hereafter Seattle) include the majority of the GB-PS population, industry and pollution. The major sources of air pollution for Vancouver and Seattle are motor vehicles, marine vessels and wood burning appliances (i.e., wood stoves and fireplaces). Although air quality in the region is generally regarded as good, both Seattle and Vancouver frequently experience temperature inversions. Stagnant air masses and the confining valley walls can produce higher than expected air pollution concentrations. Given their similar climate, topography, economic bases and sources of air pollution, Seattle and Vancouver serve as useful comparators in the burgeoning environmental justice literature and in particular allow us to address, at least in a preliminary way, ongoing debates over continental versus national urbanism in North America.

Accordingly, this paper has two purposes: First, we aim to improve the methodology of land use regression by demonstrating how we may reduce the uncertainty of selecting buffer sizes for input data in the modeling process. Second, we aim to draw some

[1] Research methods included spatial coincidence (Sheppard et al. 1999), proximity analysis (Henderson et al. 2007; Jerrett et al. 2005a), exposure index (Farias et al. 2005) and air dispersion modeling (Dolinoy and Miranda 2004). A buffer analysis is superior to the point-in-polygon method as it uses spatial proximity as a measure of risk rather than spatial coincidence (Matson 2000).

conclusions about the relative levels of environmental (in)justice in Seattle and Vancouver and thereby offer some clues to common or distinct Canada–US experiences in urban environmental justice.

Data and methods

Figure 1 shows the GB-PS common air shed including the locations of the Seattle and Vancouver metropolitan areas. The purpose is to establish a statistical correlational analysis between neighbourhood socioeconomic markers and air pollution. In order to do so we constructed a geographic information system (GIS) incorporating air-pollution estimates, road and traffic network data, land use and socioeconomic data drawn from the respective censuses. The statistical and spatial analyses relied on ArcGIS 9.1 together with SPSS 14.0, GeoDA 0.95 and S-Plus 6.2. Pollution estimates were based on NO_2 (Nitrogen Dioxide) air-pollution data collected by the BAQS research group at 116 locations in Vancouver in 2003 and by the Multi-Ethnic Study of Atherosclerosis (MESA) Air Pollution Ancillary Study of the University of Washington at 26 locations in Seattle in 2005. The road network data of Vancouver were acquired from DMTI and of Seattle from the US Bureau of Transportation Statistics. The land use data of Vancouver and Seattle were acquired from the Greater Vancouver Regional District (GVRD, now Metro Vancouver) for 2002 and from the US Environmental Protection Agency (EPA) Water Science Center for 1998. The socioeconomic status (SES) data for Vancouver were drawn from Statistics Canada's E-Stat database for 2001 and for Seattle from the US Census Bureau Factfinder for 2000.

Fig. 1 Canadian part Vancouver and Georgia Basin and the USA part Seattle and Puget Sound. The broad Vancouver region includes the Greater Vancouver Regional District and the Fraser Valley Regional District. The broad Seattle region is located inside Snohomish, King, Pierce and Kitsap County and is within the Puget Sound airshed boundary

In addition to the above data, air pollution data were collected in special sampling campaigns in the original BAQS studies as noted above. Because nitrogen oxides concentrations in Vancouver follow a seasonal cycle, we analyzed 5 years of NO_2 data from 15 regulatory monitoring stations to identify optimal sampling periods. Starting on January 1 of each year we calculated running two-week averages for the entire year, then took the means of diametric values (i.e., those separated by 26 weeks), and compared results to the annual mean at each station. In 70 out of 75 cases the combined means for February 19 to March 4 and August 20 to September 2 were within 15% of the annual value. Two other periods produced slightly better results but captured the annual mean as a product of extremes in NO_2 concentration whereas the February/March and August/September periods could each provide an independent estimate. Accordingly, our field campaigns ran from February 24 through March 14 and September 8 through September 26, 2003 (Henderson et al. 2007). During both campaigns we measured the integrated 14-day mean concentrations of NO (Nitric Oxide) and NO_2 with Ogawa passive samplers at 116 locations, located using a location-allocation algorithm (Kanaroglou et al. 2005). Spring and fall results were averaged to estimate the annual mean for each site. In addition we collocated a total of 27 samplers with regulatory chemiluminescence monitors, and collected 38 duplicates and 26 field blanks. The sampling sites covered a 2,200 km^2 area, which included a mix of land uses, ranging from the urban and industrial centers of Vancouver, to suburban including for example, golf courses and parks. To focus our study on assessment of environmental injustice we focused on the 'criterion pollutant' (one known to be associated with adverse health effects) NO_2.

Field monitoring of community-level NO_X (nitrogen oxides) concentrations at 26 locations in Seattle was performed as part of the MESA Air pilot study (Cohen 2005). The sampling of NO_X was primarily undertaken to refine a field sampling protocol for the MESA Air study, with the majority of sampling locations being clustered near major highways and streets to capture concentration gradients. Most samplers were placed between 5 and 350 m from three target roadways (one highway and two major arterial roads) oriented in different directions. Additional samplers were deployed to complete a grid-like pattern throughout the north end of Seattle. One sampler was collocated with the Washington State Department of Ecology's (WDOE) continuous NO_X analyzer on Beacon Hill, and three duplicates were collected. Samplers were located approximately 2.5 m above the ground on telephone or utility poles. All samplers were deployed on 3 March 2005 and retrieved on 17 March.

With these data inputs LUR seeks to first parameterize a spatial model of ambient pollution concentrations that is then used to produce estimates across the entire urban field. LUR predicts long-term average pollution concentrations at a given site based on surrounding land use and traffic characteristics (Jerrett et al. 2005a). Measured pollutants are regressed against data on the road network, traffic volume, land cover, altitude and other locally determined features. The main strength of LUR is the empirical structure (e.g., selection of optimized buffer size) of the regression mapping and its relatively simple inputs/low cost (as compared with dispersion modeling, for example; Jerrett et al. 2005a). However, for LUR, the methods developed to analyze intra-urban exposure contrasts are based on circular buffers drawn around sites of interest to (1) extract covariates for calibrating models of ambient concentrations with data at measurement sites and then (2) estimate values at un-sampled locations across the entire region. As such, the method is case- and area-specific (Briggs et al. 1997) and there is little theoretical–physical basis behind its application including the definition of circular buffers to extract local covariates for LUR modeling.

We aim in this paper to advance the method outlined above. To assist in selecting optimal buffer distances for local land use inputs, 50 inclusive buffers of 100 m each were drawn around each sampler such that the first buffer ranged from 0 to 100 m, the second 0 to 200 m, and so forth up to the final buffer 0 to 5,000 m. This approach permits us to examine correlations between land uses and observed air pollution values at sampled locations. For roadways the total road length inside a buffer was summed (Eq. 1). A similar approach was used to analyze population density (Eq. 2) and areal land use types (Eq. 3).

$$L_{i,j} = \sum_{k=1}^{m} L_{i,j,k}, \text{ for high way and major road length} \quad (1)$$

$$D_{i,j} = \frac{\sum_{k=1}^{m} \left(\frac{S_{i,j,k}}{S_k} * X_k \right)}{\sum_{k=1}^{m} S_{i,j,k}}, \text{ for population density} \quad (2)$$

$$S_{i,j} = \sum_{k=1}^{m} \left(\frac{S_{i,j,k}}{S_k} \right), \text{ for area of a land use type} \quad (3)$$

$L_{i,j}$, $D_{i,j}$, and $S_{i,j}$ are respective total highway or major road length (m), population density (per ha) and area of a land use type (ha) inside buffer distance j ($j = 100, 200, \ldots, 5{,}000$ m) of the ith sampler. $L_{i,j,k}$ represents the highway or major road length of the kth segment inside buffer j of the ith sampler. $S_{i,j,k}$ is the intersected area (ha) between the kth CT (or land use polygon) and buffer of distance j. S_k is the area (ha) of the kth CT (or land use polygon). X_k is the total population inside the kth CT.

The road length, population density and area of a land cover within each of the 50 buffers were calculated and their correlations with NO_2 were estimated (Fig. 2a and 2b). The X-axis represents buffers running from 0 to 100, 0 to 200, …, 0 to 5,000 m from the sampler. The correlations peaked at different buffer distances for different predictors. Overall, the correlations for Vancouver vary dramatically for buffers within 2,000 m and then climb only slowly to plateau from 3,500 to 5,000 m. Seattle showed more variability and no apparent plateau for most of the predictors. A plateau demonstrates that a spatial correlation reaches its maximum distance of influence. Residential land use showed inconsistent signs of correlation for both areas and was therefore removed from our model selection. The signs of correlation of major road length in Seattle also showed inconsistency and were removed from the analysis.

Based on Fig. 2a (Vancouver), highways showed high correlations from buffer distance 500 m to 1,200 m. Highway 1,000 m (Hwy_{1000}) was among the highest and therefore selected for the land use model for Vancouver. Major roads included three apparent peaks: buffer distances 400 ($Mjrd_{400}$), 1,000 and 2,500 m, and these three distances were selected for our prediction model. Population density showed a typical population growth shape—rapid increase for buffers with distance below 500 m and little increase beyond this. Buffer distance 3,000 m ($PopDen_{3000}$) was a representative point of the plateau and was selected to calculate population density for our prediction model. As to the correlation between a land use (ha) and its NO_2, commercial, industrial and transportation-communication-utilities peaked at buffer distances of 400/3,800 ($Comm_{400}$ and $Comm_{3800}$), 1400 (Ind_{1400}) and 3,000 m ($Trans_{3000}$), respectively. A final land use model for Vancouver by road network, population density and land use types used these buffers plus elevation (*Elev* in meter) in a stepwise procedure (covariate significant level at 0.05) to predict NO_2 as shown in Eq. 4. The model was significant at the 0.01 level ($p < 0.01$ and $R^2 = 0.58$). For comparison this model differs from that developed by Henderson et al. (2007) in the original LUR sampling campaign:

$$\begin{aligned} NO_2 = {} & 10.744 + 0.0002 * Hwy_{1000} + 0.001 \\ & * Mjrd_{400} + 0.142 * Comm_{400} + 0.015 \\ & * Ind_{1400} + 0.007 * Trans_{3000} + 0.108 \\ & * PopDen_{3000} - 0.015 * Elev \end{aligned} \quad (4)$$

Based on Fig. 2b (Seattle), highway correlations peak at buffer distance 1,800 m (Hwy_{1800}). With buffer distances below or above that, a significant decrease was observed, especially for distances greater than 1,800 m. Highway 1,800 m was therefore selected for the land use model for Seattle. Major road and residential land use showed inconsistency in correlations and were removed from the model covariates list. Population density showed a similar pattern to Vancouver and buffer distance 2,500 m ($PopDen_{2500}$) had a relatively higher correlation compared to its neighboring buffers. Population buffer distance 2,500 m was selected to represent its population density effect. Among land use types, commercial land use was found to rise rapidly in correlation with NO_2 peaking at the selected buffer distance of 500 m ($Comm_{500}$). After a modest correlation from 1,000 m to 2,000 m, the highest correlation at buffer distance 2,000 m for industrial land use was selected. Transportation-communication-utilities (*Trans*) had the highest correlation among the selected variables; however, *Trans* was found mainly distributed along highways in Seattle. These two arrays of correlations (with NO_2) were highly correlated ($r = 0.97$)

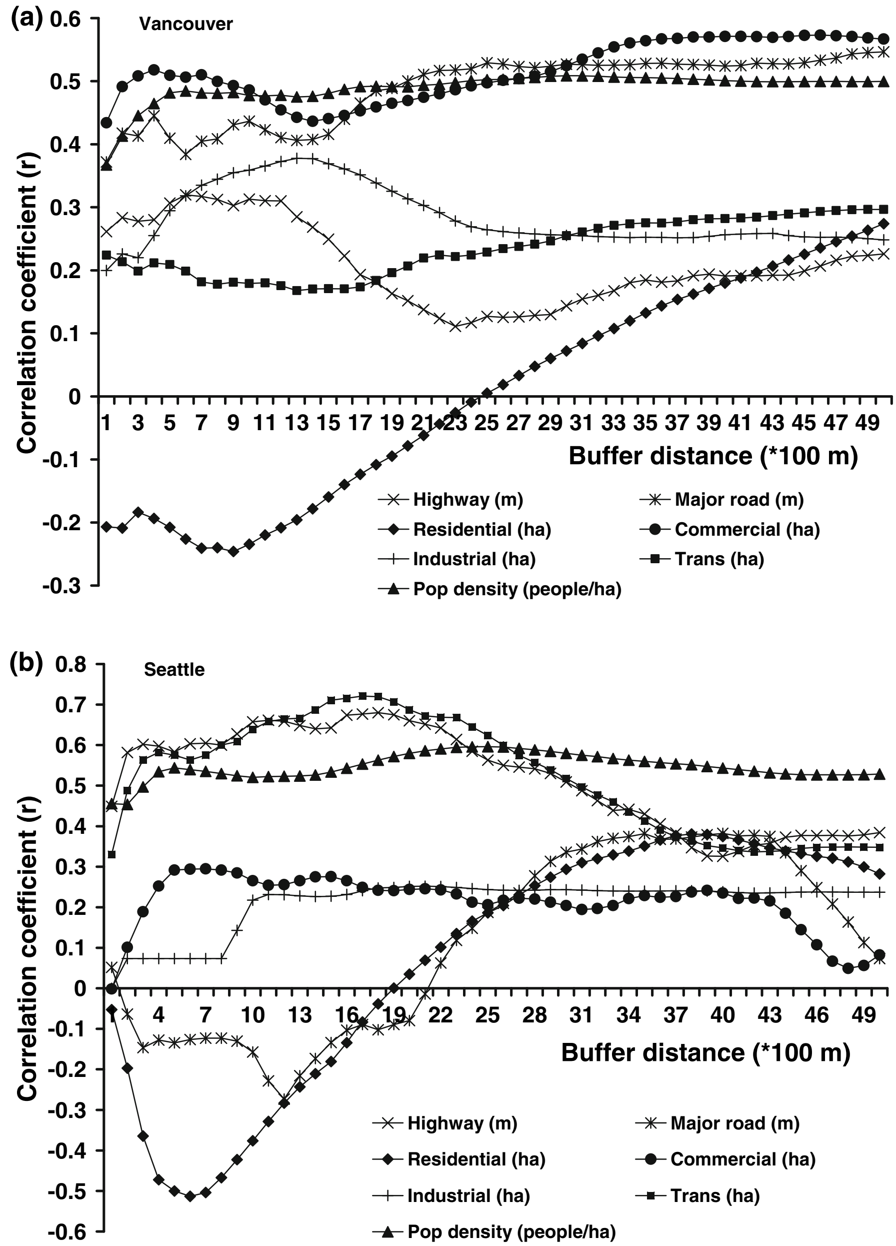

Fig. 2 Correlation matrices of road network, population density and land uses for Vancouver (**a**) and Seattle (**b**) with buffer distances 100–5,000 m

(Fig. 2b). Because our purpose was to model the spatial distribution of NO_2, highway rather than *Trans* was used as a predictor. A final land use model for Seattle used the above chosen buffers plus elevation (*Elev* in meter) in a stepwise procedure (covariate significant level at 0.05) to predict NO_2 and the model is shown in Eq. 5. The model was significant at the 0.01 level ($p < 0.01$ and $R^2 = 0.67$). Similar to Eq. 4, no spatial coordinates were used for the prediction model:

$$NO_2 = 10.653 + 0.0004 * Hwy_{1800} + 0.061 * Comm_{500} + 0.114 * PopDen_{2500} \quad (5)$$

Equations 4 and 5 were then used to estimate NO_2 concentrations for Vancouver and Seattle respectively. Census tract mean NO_2 concentrations were then used in the environmental injustice analysis with selected tract social economic status (SES) variables hypothesized to be significant based on past research.

These included race (white, black, Asian and visible minority composition), education attainment, lone parent family, labor force in manufacturing, unemployment rate, poverty, average income, median income, average family income, median family income, average household income and median household income. Stepwise ordinary least square (OLS) regression was used to include all the SES variables chosen above with *p* significant at the 0.05 level. The correlation of each SES variable with NO_2 was investigated first and variables were kept if they took the hypothesized/expected sign in both correlation and OLS models. To test the efficacy of the prediction models, we evaluated whether selected variables were collinear based on variance inflation factors (VIFs) and whether the model results had spatial autocorrelation (Buzzelli et al. 2003). If the models display spatial autocorrelation, least squares estimators may be biased and inconsistent; an aspect of spatial data that ought to be addressed in multivariate regression (Getis 1990). Associations at the CT level were therefore tested with not only a multiple OLS but also spatial autocorrelation removal algorithms—Lagrange Multiplier (LM) spatial lag/error (Anselin 2005) and generalized additive models (GAM). All models were tested with standard diagnostics and for spatial autocorrelation in the model residuals with Moran's local *I* statistic (Anselin 1995). A first-order queens-contiguity matrix was used to define statistical neighborhood dependence. If the spatial autocorrelation still exists after the spatial lag or error model, a GAM including a loess function of census-tract centroids (Burnett et al. 2001) was rerun using spatial covariates from the LM spatial lag/error model to ensure that the model did not violate the independent-observations assumption. If the spatial lag/error model and GAM all fail, a first-order rook-contiguity (Anselin 2005) was used as an alternative to define neighborhood dependence and the sensitivity analysis was rerun. In sum all of these steps are meant to reduce the influence of spatial autocorrelation in order to clarify the substantive interpretation of model results.

Finally, in addition to generating models for Seattle and Vancouver separately we also pooled their data for a combined analysis for more direct comparison. Income variables were standardized separately for Vancouver and Seattle, using the mean income value before pooling. Furthermore, we were interested not only in analyzing environmental injustice at the CT scale across both regions but also in identifying and analyzing air pollution hot spots: CT level mean NO_2 in the top tertile.

Results

Analysis of NO_2 surfaces

Figure 3 shows estimated NO_2 surfaces and regional views of NO_2 distributions in Vancouver and Seattle. In general these figures highlight the short-range variability of NO_2 concentrations. The top surfaces in Fig. 3a and 3b are respective distributions of estimated NO_2 for Vancouver and Seattle. The bottom surfaces are their respective tertile distributions aggregated by mass mean at the CT level. Figure 3a shows that Vancouver has high concentrations of NO_2 at three clustered areas: (1) Downtown Vancouver, Burrard Inlet and along Kingsway Ave, (2) the Vancouver International Airport and the northern Richmond neighborhoods, and (3) the Fraser River coastal areas along New Westminster. Seattle had peaks of NO_2 concentration mostly along interstate and state highways. Because the interstate and state highways are densely located on the west side of King County, so are the highest concentrations of NO_2. The southwest part of Snohomish and the northern section of Pierce also demonstrate high concentrations of NO_2 because of high emissions from highway traffic. In spite of all the differences, the highest NO_2 were within three times of the lowest, both in Vancouver and Seattle, for the large majority of the locations.

Table 1 displays the modeling results for Vancouver, Seattle and both pooled. Emphasized here is that the SES variables in the OLS stepwise model included all the covariates considered significant. Not all the SES variables remained in the model. The stepwise method was based on the probability of F: entry for $p \leq 0.05$ and removal for $p \geq 0.10$. For Vancouver's 420 CTs, visible minority, population in poverty and median household income were found significant. The average VIF was 1.52 with the maximum VIF being 1.95, demonstrating a lack of significant collinearity between the chosen spatial covariates. Though the fit of the stepwise model was moderate ($R^2 = 0.41$, $p < 0.001$), it produced

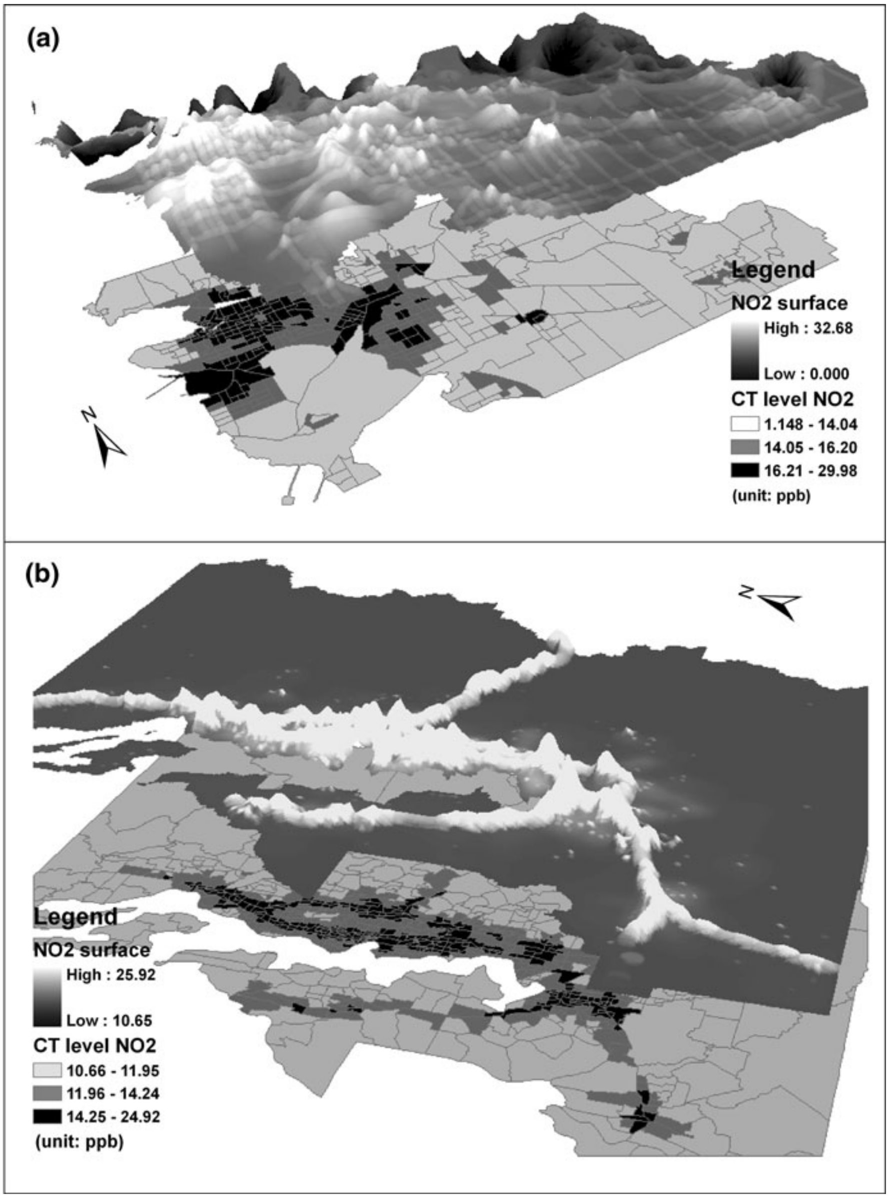

Fig. 3 Estimated NO_2 surfaces for Vancouver (upper) and Seattle (lower)

significant spatial autocorrelation (Moran's $I = 0.508$). A regression with a LM spatial lag test was found appropriate and applied to adjust for the significant spatial dependence among those covariates. Median household income and poverty remained significant.

In Seattle's 770 CTs median household income, immigrant composition, manufacturing employment and poverty were significant. However, manufacturing employment was found significantly but negatively correlated with NO_2. The average VIF was 1.43 with the maximum VIF being 1.83, also demonstrating a lack of significant collinearity between the chosen spatial covariates. Again, the OLS stepwise model produced significant spatially autocorrelated errors. After removing the majority of the spatial autocorrelation (R^2 from 0.41 to 0.86, and Moran's I from 0.580 to 0.107) by a LM lag model, median household income and immigrant composition remained significant though with diminished coefficients. Manufacturing and poverty were no longer significant. A GAM model was further used to

Table 1 OLS stepwise and spatial regression (Lagrange multiplier test and GAM) models for Vancouver, Seattle and both pooled

Region	OLS stepwise model*					Lagrange multiplier test			GAM model****	
	SES Variable	Coefficient (SE)	Variance inflation factor	Model sig. R^2 (p)	Moran's I of residuals I (p**)	Coefficient (SE)	Model sig. R^2 (p)	Moran's I of residuals I (p**)	Model sig. F (p)	Moran's I of residuals I (p**)
Vancouver	Constant	18.844 (0.754)		0.41 (0.000)	0.508 (0.010)	4.839 (0.707)	0.77 (0.000)***	0.036 (0.089)		
	% Visible minority	0.043 (0.007)	1.37							
	Med household income	−0.00010 (1.04E-05)	1.52			−3.83E-05 (0.000)				
	Poverty population	0.00044 (0.00029)	1.95			0.00028 (0.00016)				
Seattle	Constant	15.833 (0.422)		0.39 (0.000)	0.580 (0.001)	2.291 (0.255)	0.86 (0.000)***	0.107 (0.001)	9.126 (0.000)	0.036 (0.06)[b]
	% Immigrants	0.127 (0.010)	1.18			0.020 (0.005)				
	Med household income	−4.77E-05 (5.52E-06)	1.65			−2.21E-05 (0.000)				
	% Population in manufacturing	−0.096 (0.015)	1.04							
	Poverty population	0.00011 (0.00033)	1.83							
Vancouver & Seattle pooled	Constant	16.186 (0.303)		0.40 (0.000)	0.603 (0.001)	3.211 (0.295)	0.82 (0.000)***	0.077 (0.01)		
	% Immigrants	0.083 (0.005)	1.04			0.009 (0.004)				
	% Black	0.040 (0.014)	1.16							
	Med household income[a]	−3.782 (0.243)	1.18			−2.39E-05 (0.000)				

[a] Data standardized to a mean of 1 for Vancouver and Seattle, respectively

[b] Uses a K-nearest neighbor algorithm

* Stepping method criteria use probability of F-entry 0.05 and removal 0.10; ** p values are results of permutation using Geoda; *** results from a spatial lag model; **** GAM model uses a 1–5 percent loess-smoothing to the weighted centroid coordinates

determine the efficiency of including both the median household income and immigrant composition as predictors. The GAM model shows both variables independently important to capturing the spatial variability of NO_2 with residuals not showing significant spatial autocorrelation.

Table 1 also shows the pooled OLS model with Vancouver's 420 CTs and Seattle's 770 CTs. Similar to the findings from the OLS models for Vancouver and Seattle, median household income, immigrant and black/African American were found significant without significant collinearity (average VIF = 1.13). After removing the majority of the spatial autocorrelation ($R^2 = 0.82$ and Moran's $I = 0.077$) by a LM spatial lag model, neighbourhoods marked by low income households and higher immigrant populations endured a disproportionate burden of pollution concentration of NO_2.

NO_2 hot spot analysis

The hot spot analysis (Fig. 3) focuses on CTs in the top NO_2 tertile classification. Table 2 shows the significance of all the SES variables used. For Vancouver, median household income and labor force in manufacturing were found significant in the OLS stepwise model and the two did not have significant collinearity (average VIF = 1.04). However, the overall variance explained was low ($R^2 = 0.13$) as compared with the regional model discussed above ($R^2 = 0.41$). Despite the significance of the stepwise model, it also produced significant spatial autocorrelation (Moran's $I = 0.485$). A regression with a LM spatial error test was applied to adjust for spatial dependence among those covariates. Median household income and manufacturing employment remained significant with the LM spatial error model however the latter variable was also inconsistent: change in the variable's coefficient sign suggests that manufacturing employment may only be marginally or spuriously correlated with ambient air pollution.

For Seattle, the 257 hotspot CTs showed a similar pattern to the wider regional model: median household income, labor force in manufacturing and poverty were all found significant and the immigrant composition was changed to Asian composition for the hotspots. Again, no significant collinearity existed between the three chosen covariates (average VIF = 1.02). Still the variance explained by the hotspots was smaller than the regional model and produced significant spatial autocorrelations (Moran's $I = 0.450$). Once again a regression with a LM spatial error test was applied. Similar to the broader Seattle analysis, the median household income and Asian population composition remained significant for the hotspots with the LM spatial error model but not for labor force in manufacturing after removing the majority of the spatial autocorrelation (R^2 from 0.26 to 0.66, and Moran's I from 0.450 to −0.096). A GAM model was further used to examine the efficiency of including both the median household income and Asian population composition as covariates. The GAM model identified these two variables as significant on NO_2 concentrations and the model residuals showed non-significant spatial autocorrelation. These analyses demonstrated that environmental injustice for the hotspots existed for low income households and Asian populations in Seattle similar to the broader regional analysis.

When all 397 hotspot CTs were pooled, the OLS stepwise model showed that median household income, labor force in manufacturing and immigrant composition were significant. No significant collinearity existed between the three covariates (average VIF = 1.07); however, the stepwise OLS model displayed significant spatial autocorrelation (Moran's $I = 0.467$, $p = 0.001$). A LM spatial error model found only median household income to be significant and the spatial autocorrelation (Moran's $I = -0.121$, $p = 0.001$) still existed. After a GAM model with 3% spatial smoothing was applied, median household income ($F = 5.98$ and $p = 0.000$) was found significant and its corresponding Moran's I statistic insignificant ($I = 0.063$, $p = 0.06$). Similar to the findings for the broader pooled regional analysis, median household income for the hotspots remained significant in the separate Vancouver, Seattle and pooled models.

Discussion and conclusions

The regression models for Vancouver and Seattle, both separately and pooled, supplied varied estimates in the association between NO_2 and SES. The empirical results allow us to first underscore the importance of advancing LUR by using variable

Table 2 OLS stepwise and spatial regression (Lagrange multiplier test and GAM) models for hot spots in Vancouver, Seattle and both pooled

Region	OLS stepwise model*					Lagrange multiplier test			GAM model****	
	SES Variable	Coefficient (SE)	Variance Inflation Factor	Model sig. R^2 (*p*)	Moran's I of residuals I (*p***)	Coefficient (SE)	Model sig. R^2 (*p*)	Moran's I of residuals I (*p***)	Model sig. F (*p*)	Moran's I of residuals I (*p***)
Vancouver	Constant	17.944 (0.522)		0.13 (0.000)	0.485 (0.001)	14.447 (1.030)	0.66 (0.000)****	−0.093 (0.085)		
	% Population in manufacturing	−0.153 (0.051)	1.04			0.093 (0.045)				
	% Population in poverty	0.066 (0.017)	1.04			0.033 (0.014)				
Seattle	Constant	19.669 (0.461)		0.26 (0.000)	0.450 (0.001)	15.77 (0.625)	0.66 (0.000)****	−0.096 (0.016)	6.96 (0.000)	−0.034 (0.25)
	% Asian	0.046 (0.013)	1.02			0.035 (0.013)				
	Med household income	−4.683E-05 (7.71E-06)	1.03			−3.35E-05 (0.000)				
	% Population in manufacturing	−0.128 (0.025)	1.01							
Vancouver & Seattle pooled	Constant	20.147 (0.426)		0.36 (0.000)	0.467 (0.001)	16.621 (0.564)	0.73 (0.000)****	−0.121 (0.001)	5.77 (0.000)	0.067 (0.06)
	% Immigrants	0.039 (0.006)	1.10							
	Med household income[1]	−2.075 (0.377)	1.01			−2.201 (0.314)				
	% Population in manufacturing	−0.160 (0.020)	1.10							

Definitions are the same as in Table 1

buffer analyses to select substantive predictors. We also return to our overarching question of environmental justice as a uniquely national or common continental urban experience.

In general the results show that for both Vancouver and Seattle we have different sets of substantive neighbourhood markers associated with NO_2. Broader regional analyses produced more varied sets of variables and stronger model fit given their variability as compared with the hotspot analyses. Neighbourhoods marked by lone parent families did not show significant environmental injustice in Vancouver and Seattle. Like some environmental justice and urban studies (Anderton et al. 1994; Buzzelli et al. 2003), we included the manufacturing employment variable to control for the potential residential choice among lower status populations living near higher pollution zones. However, it was also found non-significant in most of the cases after removing spatial autocorrelations. Where significant in the OLS models, manufacturing employment was found negatively rather than positively associated with NO_2. This is because the spatial distribution of manufacturing industries in Vancouver and Seattle is moving toward suburbs and shifting to a post-Fordist light-manufacturing sector. Industrial and spatial restructuring may have rebalanced aggregate pollution away from the city and toward the suburbs, which can only be intensified by attendant vehicular trips and emissions (Buzzelli et al. 2003). Finally as shown a mix of variables across models included neighbourhood markers of race/visible minority status. These are important though again perhaps less telling given their relative inconsistency.

By contrast and despite changing variable sets and model fit, the most consistent and robust covariate of NO_2 was median household income (inverse relations). This variable provides an accurate representation of the wealth and asset holdings of typical households. This result corroborates Evans and Kantrowitz (2002) who documented evidence of inverse relations not only between income and ambient air pollutants but also between income and a range of environmental hazards including hazardous wastes, ambient noise and residential crowding. Blodgett (2006), Faber and Krieg (2002), Evans and Marcynyszyn (2004) and Porter and Tarrant (2001), all found median household income an important marker of environmental injustice. The common GB-PS airshed provides a useful window on the question of urban similarities and differences between American and Canadian cities. In this context perhaps the most important result is that environmental justice, having begun as a social movement and research literature in the United States, may share common lineaments in Canadian cities not in terms of race—the dominant explanator in this literature to date—but in terms of neighbourhoods marked by low income.

In general these results point to a number of areas for further inquiry and conceptual development. First, the presence of injustice in Vancouver connects with the U.S. justice research and thereby builds on the small but growing literature that dispels Canadian urban exceptionalism (Jerrett and Eyles 1997; Jerrett et al. 2001; Wakefield et al. 2001). Urban environmental justice, at least when related to air pollution exposures and putative health effects, would appear to be as much a health and environment policy issue in Canada as it is in the United States (Buzzelli et al. 2003). Second, despite their similarities there are some differences in the substantive results between Seattle and Vancouver. Immigration proved less important for its association with air pollution in Vancouver, a notable Canadian immigrant gateway, whereas it was found significant in Seattle in both the regional and hot spot analyses. Although this difference is surprising, it could be understood as the product of historical residential and labor-market segregation. The temporal relations of industrialization and residential segregation have created a geographically specific immigrant population in areas like central and southern Richmond in Vancouver. The immigrant and Asian American populations in Seattle mostly resided closer to industrial lands and highways (see Krieg 2005). This could explain why in this case income is a more significant explanator than race in pooled models of both cities. Future research could explore this particular historical-geographical context in more detail. Unlike Seattle, the City of Vancouver's history of aversion to core-area expressways (Siemiatycki 2005) may represent an important difference as compared with Seattle such that, at least related to this land use type, there are fewer neighbourhood-to-neighbourhood land rent gradients. As a result there may be fewer opportunities for recent immigrants to concentrate in less expensive neighbourhoods in central Vancouver as compared with Seattle. Further research can delve deeper into the question of comparability to shed more light on the significance of similarities, whether based on income or otherwise, or the case-dependent results of comparative environmental justice research.

Acknowledgements This research was funded by the BC Centre for Disease Control, via an agreement with Health Canada as part of the U.S.–Canada Border Air Quality Strategy. We thank the staff at the University of British Columbia and the University of Washington for their assistance with NO_X sampling and subsequent analysis. Special thanks also go to the Multi-Ethnic Study of Atherosclerosis (MESA) Air Pollution Ancillary Study at the University of Washington for their support on authorizing usage of the traffic pollution data for Seattle.

References

Anderton, D., Anderson, J., Oakes, J., & Fraser, M. (1994). Environmental equity: The demographics of dumping. *Demography, 31*, 229–248.

Anselin, L. (1995). Local indicators of spatial autocorrelation—LISA. *Geographical Analysis, 27*, 93–115.

Anselin, L. (2005). Exploring spatial data with GeoDa: A workbook. Retrieved August 9, 2007 from http://www.sal.uiuc.edu/stuff/stuff-sum/pdf/geodaworkbook.pdf.

Apelberg, B. J., Buckley, T. J., & White, R. H. (2005). Socioeconomic and racial disparities in cancer risk from air toxics in Maryland. *Environmental Health Perspectives, 113*, 693–699.

Bhat, V. (2005). Polluting facilities and environmental justice—a study. *International Journal of Environmental Studies, 62*, 5–13.

Blodgett, A. D. (2006). An analysis of pollution and community advocacy in 'cancer alley': Setting an example for the environmental justice movement in St James Parish, Louisiana. *Local Environment, 11*, 647–661.

Brauer, M., Hoek, G., van Vliet, P., Meliefste, K., Fischer, P., Gehring, U., et al. (2003). Estimating long-term average particulate air pollution concentrations: Application of traffic indicators and geographic information systems. *Epidemiology, 14*, 228–239.

Briggs, D. J., Collins, S., Elliott, P., Fischer, P., Kingham, S., Lebert, E., et al. (1997). Mapping urban air pollution using GIS: A regression based approach. *International Journal of Geographic Information Sciences, 11*, 699–718.

Brown, P., Mayer, B., Zavestoski, S., Luebke, T., Mandelbaum, J., & McCormick, S. (2003). The health politics of asthma: Environmental justice and collective illness experience in the United States. *Social Science and Medicine, 57*, 453–464.

Bullard, R. D. (1990). *Dumping in Dixie: Race, class, and environmental quality*. Boulder: Westview Press.

Burnett, R., Ma, R., Jerrett, M., Goldberg, M., Cakmak, S., Pope, C., I. I. I., et al. (2001). The spatial association between community air pollution and mortality: A new method of analyzing correlated geographic cohort data. *Environmental Health Perspectives Supplements, 109*, 375–380.

Buzzelli, M., & Jerrett, M. (2004). Racial gradients of ambient air pollution exposure in Hamilton, Canada. *Environment & Planning A, 36*, 1855–1876.

Buzzelli, M., Jerrett, M., Burnett, R., & Finklestein, N. (2003). Spatiotemporal perspectives on air pollution and environmental justice in Hamilton, Canada. *Annals of the Association of American Geographers, 93*, 557–573.

Buzzelli, M., Su, J. G., Le, N., & Bache, T. (2006). Health hazards and socio-economic status: A neighbourhood cohort approach, Vancouver, 1976–2001. *The Canadian Geographer, 50*, 376–391.

Cohen, M. (2005). *Design of the "MESA Air" prospective cohort study*. Tucson, Arizona: International Society of Exposure Analysis. Oct 30–Nov 3, 2005.

Cummins, S., Stafford, M., Macintyre, S., Marmot, M., & Ellaway, A. (2005). Neighbourhood environment and its association with self rated health: Evidence from Scotland and England. *Journal of Epidemiology and Community Health, 59*, 207–213.

Derezinski, D. D., Lacy, M. G., & Stretesky, P. B. (2003). Chemical accidents in the United States, 1990–1996. *Social Science Quarterly, 84*, 122–143.

Dolinoy, D. C., & Miranda, M. L. (2004). GIS modeling of air toxics releases from TRI-reporting and non-TRI-reporting facilities: Impacts for environmental justice. *Environmental Health Perspectives, 112*, 1717–1724.

Evans, G., & Marcynyszyn, L. A. (2004). Environmental justice, cumulative environmental risk, and health among low- and middle-income children in upstate New York. *American Journal of Public Health, 94*, 1942–1944.

Evans, G. W., & Kantrowitz, E. (2002). Socioeconomic status and health: The potential role of environmental risk exposure. *Annual Review of Public Health, 23*(1), 303–331.

Faber, D. R., & Krieg, E. J. (2002). Unequal exposure to ecological hazards: Environmental injustices in the commonwealth of Massachusetts. *Environmental Health Perspectives Supplements, 110*, 277–288.

Farias, P., Echavarria, M., Hernandez-Avila, M., Villanueva, C., Amarasiriwardena, C., Hernandez, L., et al. (2005). Bone, blood and semen lead in men with environmental and moderate occupational exposure. *International Journal of Environmental Health Research, 15*, 21–31.

Gee, G. (2004). Environmental health disparities: A framework integrating psychosocial and environmental concepts. *Environmental Health Perspectives, 112*, 1645–1653.

Getis, A. (1990). Screening for spatial dependence in regression analysis. *Papers of the Regional Science Association, 69*, 69–81.

Green, R. S., Smorodinsky, S., Kim, J. J., McLaughlin, R., & Ostro, B. (2004). Proximity of California public schools to busy roads. *Environmental Health Perspectives, 112*, 61–66.

Helfand, G. E., & Peyton, L. J. (1999). A conceptual model of environmental justice. *Social Science Quarterly, 80*, 68–83.

Henderson, S. B., Beckerman, B., Jerrett, M., & Brauer, M. (2007). Application of land use regression to estimate long-term concentrations of traffic-related nitrogen oxides and fine particulate matter. *Environmental Science and Technology, 41*, 2422–2428.

Jerrett, M., Arain, A., Kanaroglou, P., Beckerman, B., Potoglou, D., Sahsuvaroglu, T., et al. (2005a). A review and evaluation of intraurban air pollution exposure models. *Journal of Exposure Science and Environmental Epidemiology, 15*, 185–204.

Jerrett, M., Beckerman, B., Finkelstein, M., Arain, A., Kanaroglou, P., Brook, J., & Gilbert, N. (2004, May). *Spatial analysis of the relation between traffic-generated air pollution and mortality in Toronto*. Plenary speaker, Health Effects Institute, Annual Meeting, Boston, MA.

Jerrett, M., Burnett, R., Kanaroglou, P., Eyles, J., Finkelstein, N., Giovis, C., et al. (2001). A GIS-environmental justice analysis of particulate air pollution in Hamilton, Canada. *Environment and Planning A, 33*, 955–973.

Jerrett, M., Burnett, R. T., Ma, R., Pope, C. A., Krewski, D., Newbold, K. B., et al. (2005b). Spatial analysis of air pollution and mortality in Los Angeles. *Epidemiology, 16*, 727–736.

Jerrett, M., & Eyles, J. (1997). Environmental equity in Canada: An empirical investigation in the income distribution of pollution in Ontario. *Environment & Planning A, 29*, 1777–1800.

Kanaroglou, P. S., Jerrett, M., Morrison, J., Beckerman, B., Arain, M. A., Gilbert, N. L., et al. (2005). Establishing an air pollution monitoring network for intra-urban population exposure assessment: Alocation-allocation approach. *Atmospheric Environment, 39*, 2399–2409.

Krieg, E. J. (2005). Race and environmental justice in Buffalo, NY: A zip code and historical analysis of ecological hazards. *Society & Natural Resources, 18*, 199–213.

Lee, B. (1999). Taking neighborhoods seriously, in Does it take a Village? In A. Booth & A. Crouter (Eds.), *Community effects of children, adolescents and family* (pp. 31–40). New York: Russell Sage Foundation.

Matson, J. K. (2000). Exploring spatial methodologies in environmental risk assessment (project report). Department of Geography, University of Minnesota, Minneapolis, MN 55455.

Mirabelli, M. C., Wing, S., Marshall, S. W., & Wilcosky, T. C. (2006). Race, poverty, and potential exposure of middle-school students to air emissions from confined swine feeding operations. *Environmental Health Perspectives, 114*, 591–596.

Morello-Frosch, R., & Jesdale, B. M. (2006). Separate and unequal: Residential segregation and estimated cancer risks associated with ambient air toxics in U.S. metropolitan areas. *Environmental Health Perspectives, 114*, 386–393.

Neumann, C. M., Forman, D. L., & Rothlein, J. E. (1998). Hazard screening of chemical releases and environmental equity analysis of populations proximate to toxic release inventory facilities in Oregon. *Environmental Health Perspectives, 106*, 217–226.

Overman, H. G. (2002). Neighborhood effects in small and large areas. *Urban Studies, 39*, 117–131.

Porter, R., & Tarrant, M. A. (2001). A case study of environmental justice and federal tourism sites in southern Appalachia: A GIS application. *Journal of Travel Research, 40*, 27–40.

Ross, N., Tremblay, S., & Graham, K. (2004). Neighbourhood influences on health in Montreal, Canada. *Social Science and Medicine, 59*, 1485–1494.

Ross, Z., English, P., Jerrett, M., Scalf, R., Gunier, R. B., Smorodinsky, S., et al. (2006). Nitrogen dioxide prediction in southern California using land use regression modeling: Potential for environmental health analyses. *Journal of Exposure Science and Environmental Epidemiology, 16*, 106–114.

Sampson, R., Raudenbush, S., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 227*, 918–924.

Sheppard, E., Leitner, H., McMaster, R. B., & Tian, H. (1999). GIS-based measures of environmental equity: Exploring their sensitivity and significance. *Journal of Exposure Analysis and Environmental Epidemiology, 9*, 18–28.

Siemiatycki, M. (2005). The making of a mega project in the Neoliberal City: The case of mass rapid transit in Vancouver Canada. *City, 9*, 67–83.

Su, J. G., Brauer, M., & Buzzelli, M. (2008). Estimating urban morphometry at the neighborhood scale for improvement in modeling long-term average air pollution concentrations. *Atmospheric Environment, 42*, 7884–7893.

United Church of Christ Commission for Racial Justice (UCCCRJ). (1987). Toxic wastes and race in the United States: A national report on the racial and socio-economic characteristics of communities with hazardous waste sites. United Church of Christ, NY.

U.S. General Accounting Office (GAO). (1982). *The elderly remain in need of mental health services*. Gaithersburg, MD: Publication #GAO/HRD-82-112.

Wakefield, S. E., Elliott, S. J., Cole, D. C., & Eyles, J. D. (2001). Environmental risk and (re)action: Air quality, health, and civic involvement in an urban industrial neighbourhood. *Health and Place, 7*, 163–177.