Transboundary air pollution and environmental justice: Vancouver and Seattle compared

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Abstract

This paper comparatively analyses 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 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.

Key words: Transboundary, environmental justice, land use regression, spatial dependency, lagrange multiplier, generalized additive model.

Background

Twenty years ago the publication of several studies (US GAO, 1982; UCC, 1987; Bullard, 1990) founded research in what has come to be known as environmental justice. These research and social movement have attracted continued interest in the societal distribution of environmental bads such as air pollution and residential proximity to hazardous waste facilities (Helfand and Peyton 1999; Gee 2004). These disadvantaged communities are defined in different ways including low-income (Evans and Kantrowitz 2002), ethnic minorities (Bhat 2005; Green et al. 2004; Morello-Frosch and Jesdale 2006), unemployment (Cummins et al. 2005), low education (Buzzelli et al. 2006), lone-parent families (Buzzelli et al. 2003) and income and race (Apelberg et al. 2005; Mirabelli et al. 2006).

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 entire cities (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 comare 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; Sampson et al. 1997). 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 modelling (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). Recent studies show that regression mapping, or land use regression (LUR), using road length and land use categories could 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 land use regression and buffering for assessments of mortality of traffic-related air pollution for Toronto, Canada, and of 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 pick up ones thought to be the highest correlation. We argue that this method might not reflect the best buffer selection.

As part of the Canada-United States Border Air Quality Strategy (BAQS) which aims to address health issues related to air pollution in GB - PS, air pollution sampling data have been used for the present environmental justice analysis. The Greater Vancouver Regional District (GVRD, hereafter referred to as Vancouver) and the Seattle

Metropolitan Statistical Area (SMSA, hereafter referred to as Seattle) consist of the majority of the population, industry and pollution. The major sources of air pollution for Vancouver and Seattle are motor vehicles, marine vessels, wood stoves and fireplaces. Although air quality in the region is generally regarded as good, both Seattle and Vancouver frequently experience temperature inversions. The stagnant air mass and the confining valley walls keep pollutants from being dispersed and can lead to high levels of air pollution. 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 ongoing debates over continental versus national urbanism in Canada and the US.

Accordingly, this paper has two purposes: First, we aim to improve the methodology of land use regression by demonstrating how we may improve the uncertainty of selecting buffer sizes for input data in the modeling process. Second, we aim to draw some conclusions about the relative levels of environmental (in)justice in Seattle and Vancouver and thereby offer some clues to possible Canada-US differences in urban environmental justice.

Data and Methods

Figure 1 shows the GB-PS common air shed including the locations of Seattle and Vancouver metropolitan areas. 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 for the Multi-Ethnic Study of Atherosclerosis (MESA) Air Pollution Ancillary Study at the University of Washington at 26 locations 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) office for 2002 and from the US Environmental Protection Agency (EPA) Water Science Center for 1998. The SES data for Vancouver were drawn from Statistics Canada's E-Stat service for 2001 and for Seattle from the US Census Bureau Factfinder for 2000.

The NO_2 measurements used in this research were part of a nitrogen oxides (NO_x) air quality monitoring campaign for the GVRD (Henderson et al. 2007), which included 116 samplers located using a location-allocation algorithm (Kanaroglou et al., 2005). Briefly site selection was aimed at maximizing the variability in measured pollutant concentrations. Measurements for this study used data averaged from two field campaigns that ran from Feb 24 through Mar 14 and Sep 8 through Sep 26, 2003, where Ogawa® passive samplers were used to collect NO (nitric oxide) and NO_2 over 14 days throughout the region. Measurement periods were specifically selected, after review of 5 years of monitoring data, to most accurately characterize long term average concentrations. The mean annual concentrations of NO_2 measured were 16.07 ppb for the metropolitan area.

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 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 modelling.

To assist in selecting the best buffer distances for local land use inputs, 50 inclusive buffers of 100m each were drawn around each sampler such that the first buffer ranged from 0-100 m, the second 0-200 m, and so forth up to the final buffer from the final buffer 0-5000 m. This approach permits us to examine the correlations between land uses and observed air pollution values at sampled locations. For roadways the total road length inside a buffer was summed. 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, …, 5000 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 (Figure 2 a and b). The X-axis represents buffers running from 0-100, 0-200, …, 0-5000 m from the sampler. The correlations peaked at different buffer distances for different predictors. Overall, the correlations for Vancouver vary dramatically for buffers within 2000 m and then climb only slowly to plateau from 3500 to 5000 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 as a factor for our model selection. The signs of correlation of major road length in Seattle also showed inconsistency and were removed from the analysis.

Based on Figure 2a (Vancouver), highways showed high correlations from buffer distance 500 m to 1200 m. Highway 1000 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 ($Mjrd_{400}$), 1000 and 2500 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 3000 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 400/3800 ($Comm_{400}$ and $Comm_{3800}$), 1400 (Ind_{1400}) and 3000 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 equation (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:

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

Based on Figure 2b (Seattle), highway correlations peak at buffer distance 1800 m (Hwy_{1800}). With buffer distances below or above that, a significant decrease was observed, especially for distances greater than 1800 m. Highway 1800 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 2500 m ($PopDen_{2500}$) had a relatively higher correlation compared to its neighboring buffers. Population buffer distance 2500 m was selected to represent its population density effect. Among land use types, commercial land use was found to rise rapdily in correlation with

NO_2 peaking at the selected buffer distance of 500 m ($Comm_{500}$). After a modest correlation from 1000 m to 2000 m, the highest correlation at buffer distance 2000 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) (Figure 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 equation (5). The model was significant at the 0.01 level ($p < 0.01$ and $R^2 = 0.67$). Similar to equation (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, respectively, to estimate NO_2 concentrations for Vancouver and Seattle. Census tract mean NO_2 concentrations were then used in the environmental injustice analysis with selected SES variables hypothesized to be significant based on past research. These included 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 the selected variables were required to have an unchanging sign (either positive or negative) in both correlation and OLS model. This approaches requres that we test model results for spatial autocorrelation (Buzzelli et al. 2003). If the data display this property, least squares estimators are biased and inconsistent. The spatial aspects underpinning many social phenomenaoften influence the results obtained in multivariate regression (Getis 1990). Spatial autocorrelation between variables in a regression framework has to be identified and addressed. 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 significant spatial autocorrelation in the model residuals with Moran's local *I* statistics (Anselin 1995). A first-order queens-contiguity matrix was used to define neighborhood dependency. 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 dependency and the sensitivity analysis was reurn again.

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, respectively, using the mean income value before pooling. Furthermore, we were interested not only in analysis

environmental unjustice at the CT scale across both regions but also in identifying and analysisng air pollution hot spots: CT mean NO_2 in the top tertile.

Results

Figure 3 shows estimated NO_2 surfaces and regional views of NO_2 distributions in Vancouver and Seattle. The top surfaces in Figure 3a and 3b are respective distributions of NO_2 estimated for Vancouver and Seattle. The bottom surfaces are their respective tertile distributions of NO_2 aggregated by a 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 Inet 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 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 the high emissions of NO_2 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.

Part I of 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, immigrants, population in poverty and median household income were found significant. Though the significance of the stepwise model

(R^2 = 0.42, p<0.001), it also produced 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 and poverty were significant. However, manufacturing population was found significantly but negatively correlated with NO_2. 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; however, their coefficients diminished. Manufacturing and poverty were no longer significant. A GAM model was further used to determine the efficiency of including both the median household income and immigrant composition as predictors. The GAM model shows both variables remain significant with residuals not showing significant spatial autocorrelation.

Table 1 also shows the pooled OLS model with the inclusion of 420 CTs in Vancouver and 770 CTs in Seattle. Similar to the findings from the OLS models for Vancouver and Seattle, median household income, immigrant and poverty variables were found significant. 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, higher immigrant populations and poverty endured a disproportionate burden of pollution concentration of NO_2.

Turning to the hot spot analysis (Figure 3), CTs of the top tertile classification for Vancouver and Seattle were analyzed. Part II of Table 1 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. However, the overall variance could be explained ($R^2 = 0.15$) by the OLS model for the hotspots were much lower than its corresponding model for the broad Vancouver region ($R^2 = 0.42$). 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 the significant spatial dependence among those covariates. The median household income and labor force in manufacturing remained significant with the LM spatial error model; however, labor force in manufacturing showed its inconsistency: the change of coefficient from negative in the OLS model to positive in the LM model. This demonstrated that labor force in manufacturing is only marginally significant.

For Seattle, the 257 hotspot CTs showed a similar pattern to its broad 770 CTs: median household income, labor force in manufacturing, poverty population were all found significant and the immigrant composition was changed to Asian composition for the hotspots. Again, the variance being explained by the hotspots was smaller than the broader Seattle region and the OLS model produced significant spatial autocorrelations (Moran's $I = 0.450$). Once againa 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 and poverty after removing the majority of the spatial autocorrelation (R^2 from 0.27 to 0.66, and Moran's I from 0.450 to -0.096).

A GAM model was further used to determine 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 modeling residual had non-significant spatial autocorrelation. These analyses demonstrated that environmental injustice for the hotspots did exist for low income households and Asian populations in Seattle similar to the broader regional analysis.

When all the 397 hotspot CTs were pooled, the OLS stepwise model once again showed that both median household income and labor force in manufacturing were significant. Immigrant and low income population compositions were also found significant for the pooled hotspots. However, the stepwise OLS model displayed significant spatial autocorrelation (Moran's I = 0.467, p=0.001). A LM spatial error test was then applied. Only median household income was found significant and the spatial autocorrelation (Moran's I = -0.121, p=0.001) still existed after the LM spatial error model (R^2 = 0.73). 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 statistics insignificant (I=0.063, p=0.06). Similar to the findings for the broad regions, the median household income for the hotspots remained significant in the separate Vancouver, Seattle and pooled models.

Discussions and Conclusions

The regression models for Vancouver and, Seattle, separately and pooled, supplied varied estimates in the association between NO_2 and SES. In one aspect, the results showed that whether NO_2 rose or fell, injustice persisted but becomes less pronounced over the hotspots (lower R^2); however, this difference almost disappeared after removing or

reducing their spatial dependence in the models. Despite changing variable sets and model fit, the most consistent and robust covariate of NO_2 was median household income (inverse relations). As noted above, the median household income provides a more accurate representation of the wealth and asset holdings of the typical households. This corroborated with Evans and Kantrowitz (2002), who documented evidence of inverse relations not only between income and ambient air pollutants, but also between income and and a range of environmental hazards including hazardous wastes, ambient noise and residential crowdings. This review was further enhanced by Blodgett (2006), Faber and Krieg (2002), Evans and Marcynyszyn (2004) and Porter and Tarrant (2001), who found median household income an important marker of environmental injustice.

Lone parent family often constitutes a “community of least resistance”. However, in this study, 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 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 found insignificant 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 are moving toward suburbs and are 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).

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 main lineaments of 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 urban 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, desipte 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 where it was found significant in Seattle at 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 created a geographically specific immigrant population in areas like central and southern Richmond in the GVRD. The immigrants and Asian American population in Seattle mostly resided closer to industrial lands and near highways. The historical residential and labor-market segregation was supported by Krieg (2005), who also demonstrated the segregation excluded African Americans from residing in industrialized sections of the city, disproportionate impact of environmental hazards occurred on lower median income households but the insignificant environmental racism of African Americans. This might help to explain why previous analyses of market dynamics by Been (1994) and Been and Gupta (1997) did not reach conclusive results. The difference also demonstrated that specific conclusions should depend on one's definition of environmental discrimination

and the levels of analysis, both spatial and temporal (Anderton et al. 1994; Bowen et al. 1995; Dolinoy and Miranda 2004; Downey 1998).

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References

Anderton, D., Anderson, J., Oakes, J., Fraser, M. (1994). Environmental equity: The demographics of dumping. *Demography*, 31, 229–48.

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.

Been, V, Gupta, F. (1997). Coming to the nuisance or going to the barrio? A longitudinal analysis of environmental justice claims. *Ecology Law Quarterly*, 24, 1-56.

Been, V. (1994). Locally undesirable land uses in minority neighborhoods: Disproportionate sitting or market dynamics? *Yale Law Review*, 103, 1383.

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.

Bowen, W. M., Salling, M. J., Haynes, K. E, Cyran, E. J. (1995). Toward environmental justice: Spatial equity in Ohio and Cleveland. *Annals of the Association of American Geographers*, 85, 641-663.

Brauer, M., Hoek, G., van Vliet, P., Meliefste, K., Fischer, P., Gehring, U., Heinrich, J., Cyrys, J., Bellander, T., Lewne, M., Brunekreef, B. (2003). Estimating long-term average particulate air pollution concentrations: application of traffic indicators and geographic information systems. *Epidemiology*, 14, 228-239.

Briggs, D. J., Collins, S., Elliott, P., Fischer, P., Kingham, S., Lebert,E., Pryl, K., Van Reeuwijk, H., Small bone, K., Van Der Veen, A. (1997). Mapping urban air pollution using GIS: a regression based approach. *International Journal of Geographic Information Sciences*, 11, 699-718.

Briggs, D. J., Collins, S., Elliott, P., Fischer, P., Kingham, S., Lebert,E., Pryl, K., Van Reeuwijk, H., Small bone, K., Van Der Veen, A. (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 & 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, III C., Krewski, D. (2001). The spatial association between community air pollution and mortality: A new method of analyzing correlated geographic cohort data. *Environmental Health Perspectives Supplements*, 109, 375–80.

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.

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 & 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.

Downey, L. (1998. Environmental injustice: Is race or income a better predictor? *Social Science Quarterly*, 79, 766-778.

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

Exposure Science and Environmental Epidemiology, 16, 106–114.

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., Aro, A., Hu, H. (2005). Bone, blood and semen lead in men with environmental and moderate occupational exposure. *International Journal of Environmental Health Research*, 15, 21-31.

Farrell, A. and Keating, T. (2002). Transboundary environmental assessment: Lessons from OTAG. *Environmental Science & Technology*, 36, 2537-2544.

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 & technology*, 41, 2422-2428.

Inyang, H. I. (1999). Emergence of transboundary environmental problems (Editorial). *Journal of Environmental Engineering*, 125, 995.

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

Jerrett, M., Arain, A., Kanaroglou, P., Beckerman, B., Potoglou, D., Sahsuvaroglu, T., Morrison, J., Giovis, C. 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). Spatial analysis of the relation between traffic-generated air pollution and mortality in Toronto. Plenary speaker, Health Effects Institute, Annual Meeting, Boston, MA, May 2004.

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

Jerrett, M., Burnett, R., Kanaroglou, P., Eyles, J., Finkelstein, N., Giovis, C., Brook, J. (2001). A GIS-environmental justice analysis of particulate air pollution in Hamilton, Canada. *Environment and Planning A*, 33, 955–73.

Jerrett, M., Burnett, R.T., Ma, R., Pope, C.A., Krewski, D., Newbold, K.B., Thurston, G., Shi, Y., Finkelstein, N., Calle, E. E., Thun, M. J. 2005b. Spatial analysis of air pollution and mortality in Los Angeles. *Epidemiology*, 16, 727-736.

Kanaroglou, P.S., Jerrett, M., Morrison, J., Beckerman, B., Arain, M.A., Gilbert, N.L., Brook, J.R. (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? Community Effects of Children, Adolescents and Family. Eds A Booth, A Crouter (Russell Sage Foundation, New Yor), pp 31-40.

Matson, J. K. (2000). Exploring Spatial Methodologies in Environmental Risk Assessment (Project report). Department of Geography, University of Minnesota Minneapolis, MN 55455.

Mickelson, K. (2002). Book review: Smelter Smoke in North America: The Politics of Transborder Pollution. *Pacific Historical Review*, 71, 332-333.

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. and 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.

Moussiopoulos, N., Helmis, C. G., Flocas, H. A., Louka, P., Assimakopoulos, V. D, Naneris, C., Sahm, P. (2004). A modeling method for estimating transboundary air

pollution in southeastern Europe. *Environmental Modeling & Software*, 19, 549-558.

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. and 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, Z., English, P., Jerrett, M., Scalf, R., Gunier, R.B., Smorodinsky, S., Wall, S., (2006). Nitrogen dioxide prediction in southern California using land use regression modeling: potential for environmental health analyses. *Journal of*

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 Enzironmental Epidemiology*, 9, 18–28.

Siddiqui, A. I. and Quah, E. (2004). Modeling transboundary air pollution in Southeast Asia: policy regime and the role of stakeholders. *Environment & Planning A*, 36, 1411-1425.

Su, J.G., Brauer, M., Buzzelli, M. (2008). Application of urban micro-environmental geometry at neighborhood scale for long-term average air pollution concentrations estimation. Submitted to the journal of *Atmospheric Environment*.

U.S. General Accounting Office (GAO). (1982). *The Elderly Remain in Need of Mental Health Services*. Publication #GAO/HRD-82-112. Gaithersburg, MD.

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.

VanNijnatten, D. L. (2003). Analyzing the Canada-U.S. environmental relationship: A multi-faceted approach. *American Review of Canadian Studies*, 33, 93-120.

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.

Wakefield, S., Elliott, S., Cole, D., Eyles, J. (2001). Environmental risk and (re)action: Air quality, health, and civic involvement in an urban industrial neighbourhood. *Health and Place*, 7, 163–77.

Table 1. OLS stepwise and spatial regression (Lagrange multiplier test and GAM) models

Region	SES Variable	OLS stepwise model* Coefficient (SE)	OLS stepwise model* Model sig. R^2 (p)	OLS stepwise model* Moran's I of residuals I (p**)	Lagrange multiplier test Coefficient (SE)	Lagrange multiplier test Model sig. R^2 (p)	Lagrange multiplier test Moran's I of residuals I (p**)	GAM model***** Model sig. F (p)	GAM model***** Moran's I of residuals I (p**)
Part I – The broad Vancouver and Seattle regions : Vancouver 420 CTs and Seattle 770 CTs									
LFV	Constant	16.501 (0.944)	0.42 (0.000)	0.508 (0.010)	4.543 (0.752)	0.77 (0.000)***	0.036 (0.089)		
	% immigrants	0.051 (0.012)							
	Med household income	-8.24E-05 (0.000)			-3.42E-05 (0.000)				
	% pop in poverty	0.071 (0.023)			0.025 (0.012)				
SMSA	Constant	14.445 (0.467)	0.41 (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)[2]
	% immigrants	0.110 (0.010)			0.020 (0.005)				
	Med household income	-3.05E-05 (0.000)			-2.21E-05 (0.000)				
	% pop in manufacturing	-0.092 (0.014)							
	% pop in poverty	0.078 (0.016)							
LFV & Seattle	Constant	14.669 (0.394)	0.41 (0.000)	0.603 (0.001)	3.211 (0.295)	0.82 (0.000)***	0.077 (0.01)		
	% immigrants	0.055 (0.007)			0.009 (0.004)				
	% black	0.042 (0.014)							
	Med household income[1]	-2.644 (0.308)			-1.284 (0.165)				
	% pop in poverty	0.074 (0.013)			0.021 (0.007)				
Part II The hotspots in Vancouver and Seattle: Vancouver 140 CTs and Seattle 257 CTs									
LFV	Constant	22.707 (0.801)	0.15 (0.000)	0.507 (0.001)	17.108 (0.980)	0.68(0.000)****	-0.096 (0.085)		
	Med household income	-6.93E-05 (0.000)			-4.94E-05 (0.045)				
	% pop in manufacturing	-0.148 (0.050)			0.083 (0.043)				
SMSA	Constant	18.260 (0.822)	0.27 (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	0.040 (0.014)			0.035 (0.013)				
	Med household income	-2.89E-05 (0.000)			-3.35E-05 (0.000)				
	% pop in manufacturing	-0.119 (0.025)							
	% pop in poverty	0.045 (0.022)							
LFV & Seattle	Constant	18.852 (0.672)	0.37 (0.000)	0.467 (0.001)	16.621 (0.564)	0.73 (0.000)****	-0.121 (0.001)	5.98 (0.000)	0.067 (0.06)[2]
	% immigrants	0.026 (0.008)							

Med household income[1]	-1.746 (0.538)	-2.201 (0.314)
% pop in manufacturing	-0.144 (0.021)	
% pop in poverty	0.038 (0.015)	

* 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; ****results from a spatial error model; *****GAM model uses a 1-5 percent loess-smoothing to the weighted centroid coordinates. [1]Data standardized to a mean of 1 for Vancouver and Seattle, respectively, for the pooled data; [2] uses a K-nearest neighbor algorithm.

Figure 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.

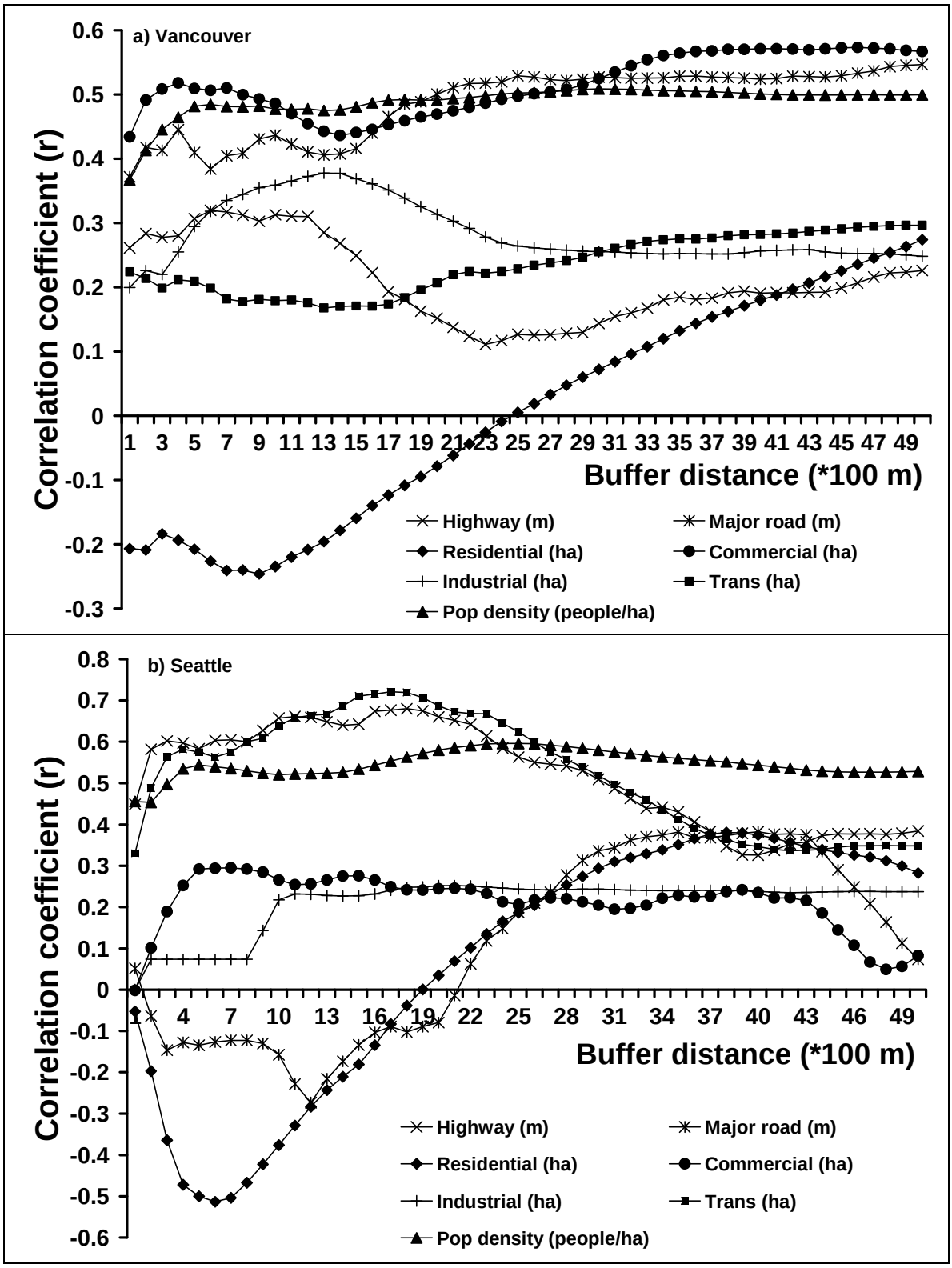

Figure 2. Correlation matrices of road network, population density and land uses for Vancouver (a) and Seattle (b) with buffer distances 100–5000 m.

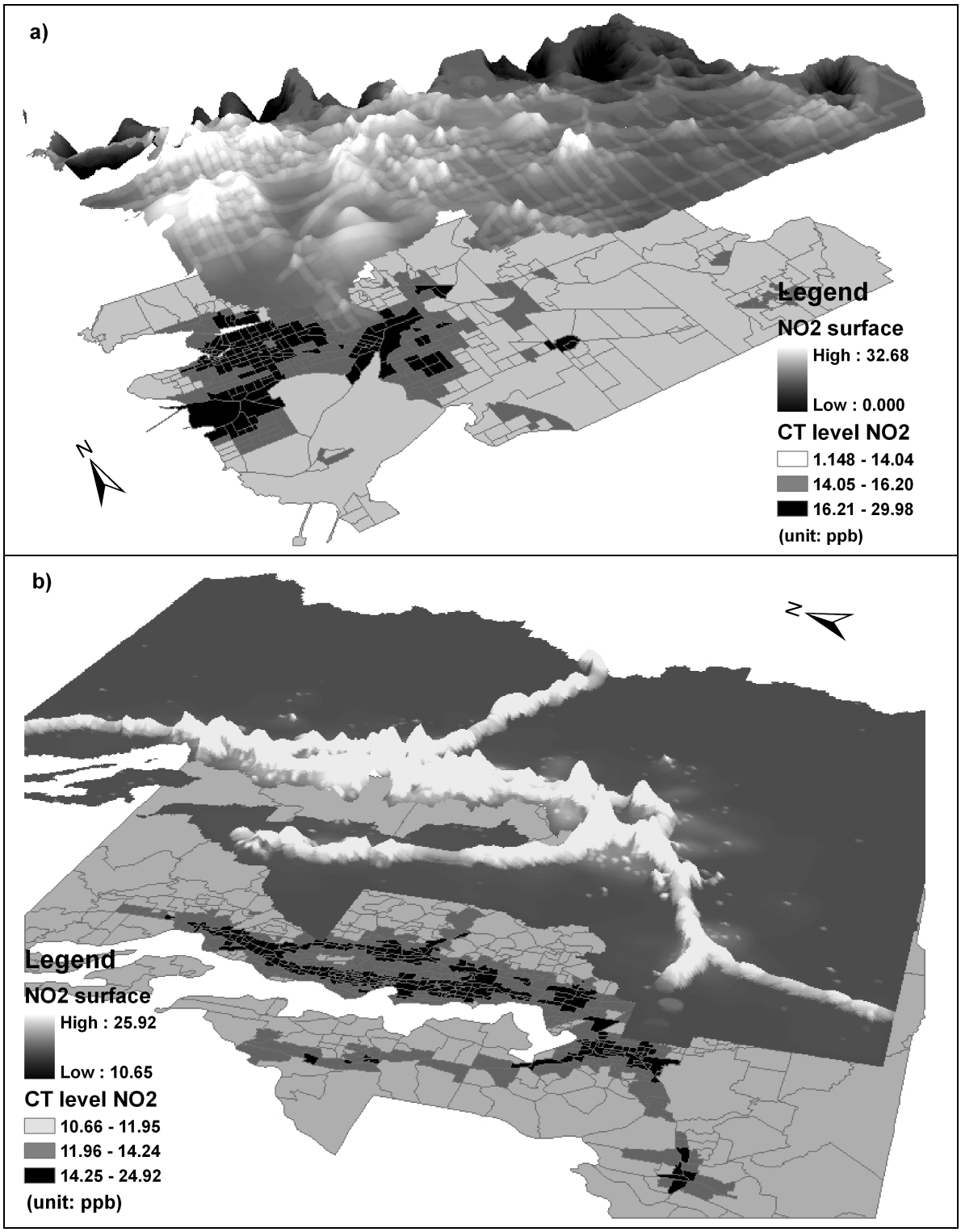

Figure 3. Estimated NO_2 surfaces for Vancouver (upper) and Seattle (lower).