Detecting the Association between Children Health and Lead Exposure Using Voronoi Polygon Rezoning

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In this paper we use Voronoi polygons (VP) to test weather more homogenous exposure areas can be generated to reduce "ecological bias". In the analysis, soil contamination measurements by Lead (Pb) were superimposed upon a layer of small census areas (SCA) and the average exposure for each SCA was calculated. Next, VPs were formed around soil test points, with each polygon containing exactly one Pb soil measurement. Spatial interpolations were also run, to compare their results with the results obtained by SCA averaging and VP rezoning. Next, OLS and Spatial Lag regressions were run to link Pb exposure with the health status of local children, with health information retrieved from the Clalit Health Services' database. Model fits were consistently higher in the VP models compared to the SCA and interpolation models, indicating that the VP method appeared to improve the models' explanatory power by reducing exposure misclassification.

Keywords: *Voronoi polygons; soil contamination; lead; GIS; exposure misclassification; ecological bias; rezoning.*

Environmental studies often use census-designated statistical areas or townships to estimate the average exposure levels of local residents to various sources of air pollution and soil contamination (Dubnov et al., 2007; Portnov et al., 2009). In most cases, the ambient levels of environmental pollutants are recorded by air quality monitoring stations (Ritz et al., 2002; Dubnov et al., 2007) or measured by soil contamination tests (Walling et al., 1999). However, census-designated areas, in which study population resides, and networks of air quality monitoring stations (AQMS) or/and soil test sites most often mismatch geographically, with some small

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census areas (SCA) hosting several environmental quality monitors, while others having none of them. This situation may lead to exposure misclassification bias, due to the fact that the same pollution exposure levels are effectively assigned to all residents of relatively large territorial units, within which actual exposure levels may vary considerably (Portnov et al., 2007; Kloog et al., 2009).

Several empirical studies attempted to address exposure misclassification bias by using various interpolation techniques, such as splines, inverse distance weighted method (IDW), kernel smoothing, and *kriging* (Wakefield ans Shaddick, 2006; Portnov et al., 2009). According to these interpolation-based approaches, discrete observations are transformed into continuous pollution surfaces, upon which residential locations of the study subjects are superimposed, thus enabling to obtain individual exposure estimates (Heuvelink, 1998). However, these interpolation techniques have several drawbacks, such as the mismatch of results obtained by different interpolation tools and "error propagation" (Gotway and Young, 2002). The major cause of the latter bias is attributed to the fact that any error (e.g., due to faulty measurements), potentially occurring at original observation points, propagates into all of the output layers of data created by interpolation distorting them (ibid,1911).

Spatial tessellation, or a division of a geographic plain into non-overlapping polygons, is another mapping technique, commonly used in geography. There are various types of spatial tessellations, such as administrative divisions, school districts, electoral districts, census tracts, vegetation patterns, land uses, and land covers. Artificial tessellations (i.e., tessellations based on regular non-overlapping shapes, not associated with particular geographic features) are also used in geography. Such tessellations include Voronoi diagrams (Voronoi polygons or Delaunay tessellations), lattices, and grids, and are used to approximate catchment areas of urban facilities or to aggregate a set of spatial features based on a common zonal system (Okabe et al., 1992).

In this paper, we hypothesize that because small census areas, used to assemble socio-economic attributes of subject populations, and actual exposure zones often mismatch geographically, this "misalliance" may lead to exposure misclassification. As we further hypothesize, using Voronoi polygons (VPs) to rezone the study area can help to generate more homogenous pollution exposure areas, thus minimizing exposure misclassification. Voronoi (or sometimes called Thiessen) polygons (VP) are regions, whose interior consists of all points in the plane which are closer to a particular point in space than to any other one (Thiessen, 1911; Voronoi and Reine, 1908; Weisstein, 2009).

As an illustration of the proposed approach, we use the results of soil tests for Lead (Pb) contamination, carried out in the Greater Haifa Metropolitan Area (GHMA) by the Israel Geological Survey in 1998-2007 (unpublished data). Lead poisoning as a health issue has been described as a "silent epidemic" (Nriagu, 1988). According to several epidemiological studies, young children are the most sensitive group to lead exposure (Bellinger et al., 1987; Mushak et al., 1989; Thornton et al., 1990).

VORONOI POLYGONS (VPS) AND THEIR USE IN EMPIRICAL STUDIES

VPs are created around a set of "reference" points on the plane, so that all locations within a given region are closer to one of the "reference" points than to any other point in the distribution (Voronoi et al. 1908; Minami and ESRI, 2000). Thus, for a set of points (a_1, a_2,..., a_n) located on a Euclidian plane, locations *x* belong to the polygon formed around point a_i, if their distances to point a_i are equal or smaller than their distances to any other reference point a_j:

$$(x - a_i) \leq (x - a_j),$$

where differences in the parentheses stand for Euclidian distances between pairs of points.

If location *x* is equidistant from a pair of points, the location will lie on the boundary of two adjacent polygons. Similarly, if *x* is equidistant from three or more points, it will form a common vertex of three or more adjacent polygons. The resulting set of polygons, defined in the above manner, forms a contiguous, non-overlapping tessellation which is unique for any given set of input points (Hwang et al. 1999).

In previous empirical studies, VPs were primarily used in computer graphics and computer simulations, in geophysics, and meteorology (Boots 1980; Braun and Sambridge, 1995; Bohm et al., 2000; Minami et al., 2000; Mostafavi et al., 2003; Ledoux and Gold, 2007; Weisstein, 2009).

Thus, Benenson and Omer (2003) used the Voronoi diagram (VD) approach for constructing continuous building coverage, in which VP were formed around individual buildings and included the buildings themselves and surrounding areas, forming a net, visually similar to residential parcellation. In a separate study (Benenson et al., 2002) used VP to create a continuous residential parcellation so as to simulate the dynamics of ethnic distribution in the Jaffa area of the city of Tel Aviv during the period 1955 -1995, using the "agent-based" modeling approach.

Hwang and colleagues (Huang et al., 2003) conducted a health survey to assess the impact of different pathways of human exposure resulting from the off-site migration of polychlorinated biphenyl (PCB) contamination in the Mohawk Indian reservation in the U.S.A. Seven methods were examined to map surface soil PCB concentrations, including the VP method. The results indicated that all methods performed well in deriving a surface soil PCB concentration estimate, although the inverse nearest neighbor approach resulted in the smallest average estimated error.

In another study (Ritz, 2002) investigated the degree of uncertainty associated with the use of spatial exposure models for air pollution assessment. They presented a modeling framework for assessing the exposure model performance and investigated the role of spatial autocorrelation for the estimation of health effects. The study used data from the Southern California Children's Health Survey. The adjacency based weight matrices were created using VPs, in which each polygon contained exactly one individual. The analysis suggested that the inclusion of residual spatial error terms improved the prediction of adverse health effects and that residual spatial errors might be used as a diagnostic for comparing models' performances.

Okabe *et al.* (1992) published a comprehensive review of approaches to the computation of Voronoi diagrams (VDs) and their empirical applications in different fields of science, including astronomy, metallurgy, ecology, economy and physical planning. One of the potential VD applications discussed in the book was a co-investigation of spatial patterns of two layers of point-like objects (such as e.g., railway stations and bookstores), aimed at determining whether their spatial patterns are mutually dependent or independent of each other. The proposed algorithm involved a two-stage analysis: first, VPs were formed around one group of objects (e.g., railway stations) and, next, nearest neighbor distances for the second group of features (e.g., book stores), falling into individual VPs, were formed around the first group of objects and co-analyzed.

Although several empirical studies carried out to date were based on the VP technique, in most of these studies, VPs were mainly used for mapping, visualization of spatial patterns, and for the formation of non-overlapping 'trade areas' or so called 'subsistence zones.' There have also been several attempts to use the VP technique for the locational optimization of public facilities and for the comparison of *bivariate* distributions of different geographically referenced objects (Okabe et al., 1992; Hwang et al., 1999; Bohm et al., 2000). However, to the best of our knowledge, no studies have been conducted yet using VPs for multivariate analysis. However, in empirical studies, there is often a need to use multivariate statistical tools, to investigate the association between several factors while taking into account potential confounders that may affect it. Hence, in the following analysis, we attempt to illustrate the use of VPs for redefining population exposure estimates for a subsequent *multivariate analysis*, in which the association between air pollution exposure estimates and asthma morbidity will be controlled by the socio-economic status of the study population and its health attributes.

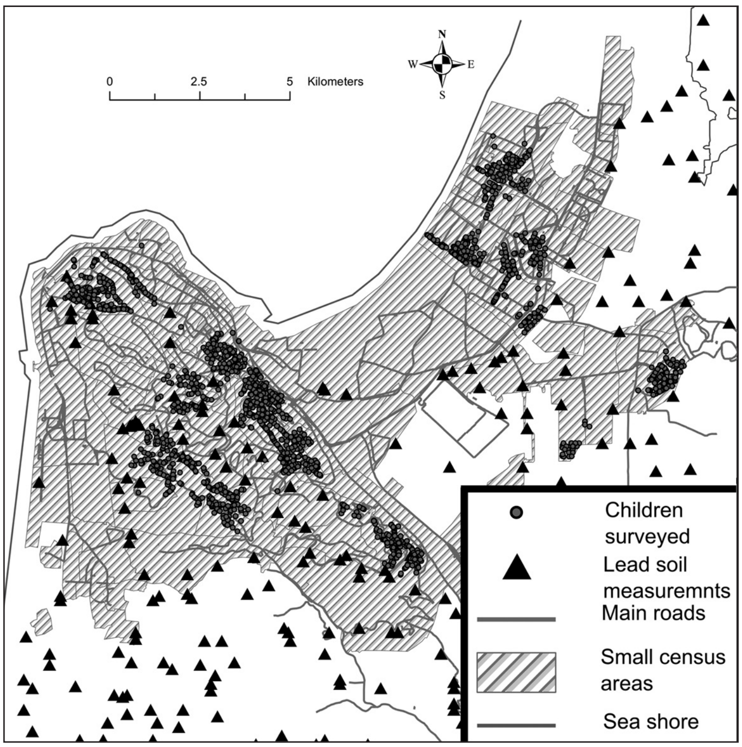
RESEARCH METHOD

Study Population

The study population consisted of a systematic sample of 3,922 schoolchildren of the 1st through 8th grade (6-14 years old) residing in different residential communities of the Greater Haifa Metropolitan Area (GHMA). The sampling was carried out in 2008-2009 by the *Clalit Health Services* (CHS) and was representative of the entire cohort of children residing in the study area in terms of gender and age (P>0.5). Geographically, our study area is formed by seven cities, including the city of Haifa (266,000 residents), Qiryat Tivon (13,100 residents), Nesher (21,300 residents), Qiryat Ata (49,600 residents), Qiryat Motzkin (39,600 residents), Qiryat Bialik (36,400 residents) and Qiryat Yam (37,000 residents). Demographic data (the date of birth, and gender) and data on the children's health status (viz., the latest measurement of weight and height; the presence of acute and chronic diseases including Asthma) were retrieved from the CHS computerized database. [CHS is the largest health care provider in Israel. Health care coverage in Israel is mandatory and all study participants had similar health insurance coverage and similar access to health services].

The locations of the children's homes were geo-coded and mapped using the ArcGIS 9.x™ software. Geocoding is the process of generating geographic coordinates (latitude and longitude) from street addresses, which enables individual locations to be mapped as GIS layers {ESRI, 2007 #10}. The residential locations of children covered by the survey are shown as small black dots on Figure 1.

Figure 1: Map of the study area showing the location of homes of children covered by the survey, lead sampling points, and SCA divisions



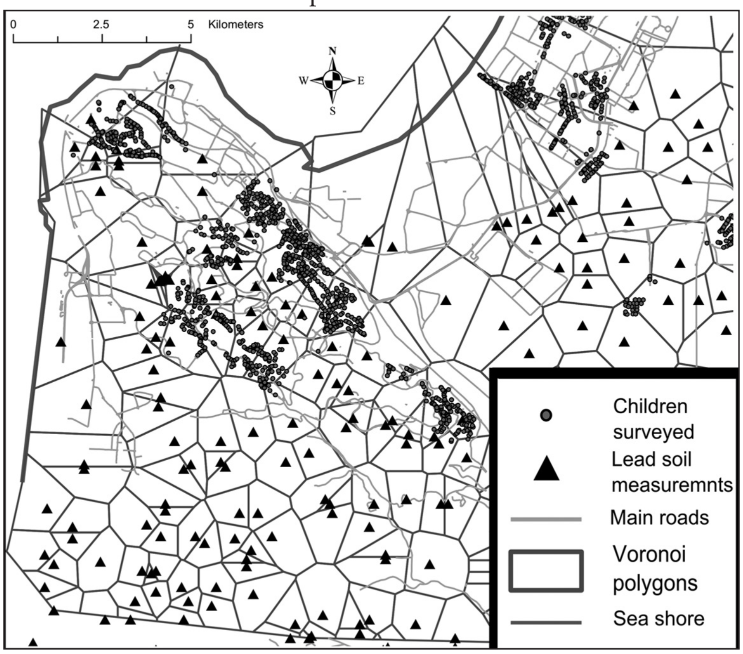
Soil Contamination Data

Soil contamination data by Lead (Pb) were obtained from the Israel Geological Survey, carried out in 1998-2007 (unpublished data). There were 45 soil sample points spread fairly evenly across the entire area of GHMA (see Figure 2) with lead contamination ranging from 0 (i.e., below detection limits) to 960 mg/kg. Although the number of soil test sites used in the analysis (45) was relatively small, this number is generally considered to be sufficient for robust spatial interpolation (Anderson, 2001). In the analysis, the default *kriging* settings (such as sill/nugget ratios) of the ArcGIS 9.x™ software were used.

Study Phases

The study was carried out in several phases. During the first phase of the analysis, soil sample points were superimposed upon the layer of SCAs, into which the entire study area is divided (see Figure 1), and the average lead exposure for each SCA was calculated. The task was performed by averaging the lead exposure values of all lead measurements falling into a given SCA. Next, VPs were formed around soil test points with each polygon containing exactly *one* lead soil measurement point (see Figure 2).

Figure 2: Voronoi polygon rezoning of the study area into exposure zones formed around soil measurement points



At the next stage of the analysis, *kriging* and Inverse Distance Weighted (IDW) interpolations were run, to compare their results with the results obtained by SCA averaging and VP rezoning. Interpolations was performed according to the individual exposure estimation approach developed in our previous studies (Yogev-Baggio et al. 2010).

Descriptive statistics of the research variables, for SCAs and Voronoi grids, are reported in Tables 1&2, respectively.

Table 1: Descriptive statistics of the research variables for the SCA resolution level*

Variable	Measurement unit	Minimum	Maximum	Mean	Std. Deviation
Dependent variable					
Asthmatic children	%	0.000	28.070	14.572	6.483
Explanatory variables					
Lead contamination	ppm	10	493	109.430	144.693
Obesity diagnosis	%	0.000	23.810	4.249	4.672
Low income status	%	0.000	50.000	10.429	10.017
Average age	years	8.833	11.333	10.082	0.435

* Total number of cases – 72.

Table 2: Descriptive statistics of the research variables for the Voronoi resolution level*

Variable	Measurement unit	Minimum	Maximum	Mean	Std. Deviation
Dependent variable					
Asthmatic children	%	0.00	37.500	13.056	7.667
Explanatory variables					
Lead contamination	ppm	16.166	173.400	70.318	41.656
Obesity diagnosis	%	0.000	16.670	3.380	4.125
Low income status	%	0.000	50.000	8.471	9.397
Average age	years	8.444	11.538	10.165	0.592

*Total number of cases – 45.

During the next phase of the analysis, individual values of lead tests were transformed in continuous surfaces using *kriging* and IDW interpolation approaches. Next, the locations of homes of children covered by the survey were superimposed upon these surfaces and individual exposure of each child in the study cohort to lead contamination was estimated. The analysis was performed using the "spatial loin" tool in the ArcGIS 9.x™ software (Minami et al., 2000; ESRI, 2007). The obtained values of lead exposure were then averaged for each SCA based on individual exposure estimates of all the children residing in each particular SCA.

During the last phase of the analysis, the percent of children with asthma, and their socio-demographic attributes were calculated, first, for the SCAs (Fig. 1), and then for the VPs (Fig. 2). Both tasks were also performed using the "spatial join" tool of the ArcGIS 9.x™ software (*ibid.*).

Statistical Analysis

To identify and measure the significance of factors affecting the development of the children's asthma, Ordinary Least Squares (OLS) models were initially used. During the analysis, multi-collinearity and normality assumptions were tested and the results were found to be satisfactory (Tolerance>0.85). The percent of children with asthma, for either SCA or VPs, was used in the analysis as the dependent variable.

In addition to lead exposure, the following factors were included into the multivariate regression analysis as explanatory variables for asthma prevalence: age, medical diagnosis of obesity (overweight), and welfare support to the child's family (presence of support for a poor family or lack thereof). The confounding role of these variables has been outlined by several previous (Smith et al., 2002; Kosti et al., 2006; Wang and Lobstein, 2006). The values of the variables were calculated for either SCAs or Voronoi divisions as percent of children with a given attribute (e.g., welfare support or obesity), apart from lead exposure and age which were calculated as averages.

During the initial stage, the analysis was performed using the following linear model:

> Percent of children with asthma = B0 (constant) + B1* (lead exposure) + B2*(age) +B3*(obesity) + B4*(low income status) + B5 (random error term), where *B0*,…, *B4* are regression coefficients.

At the second stage of the analysis, Spatial Lag (SL) regressions were run, to account for spatial dependency of regression residuals. The analysis was performed using the GeoDA 0.9© software (Minami et al., 2000).

RESULTS

Tables 3-5 report factors affecting the percent of children diagnosed with asthma and calculated using SCA averaging (Table 3), IDW and *kriging* interpolations (Table 4), and VP rezoning (Table 5). For SCA averaging and VP rezoning, two types of regression models - OLS and SL regressions - are also reported. [Since SL models obtained for interpolation-based estimates are nearly identical to the results of OLS models, SL models are not reported in Table 4, for brevity's sake].

Table 3: Factors affecting the percentage of children with asthma (geographic resolution - Small Census Areas (SCA); methods: Ordinary Least Squares (OLS) and Spatial Lag (SL) regressions)

Variable	Model 1-OLS[a]	Model 2-SL[a]
	B[a]	B[a]
(Constant)	-10.085 (-0.565)	-11.057 (-0.642)
Lead exposure	-0.008 (-1.402)	-0.007 (-1.338)
Obesity	0.067 (0.405)	0.064 (0.405)
Income status	0.127 (1.578)	0.122 (1.567)
Age	2.370 (1.347)	2.360 (1.388)
Number of obs. [b]	72	72
R^2	0.079	0.081
F	1.430	
Log likelihood		-233.21
Moran's I [c]	1.110	
Rho[d]		0.075

[a] Regression coefficient and t-statistics in the parentheses; [b] number of valid observations list-wise; [c] Moran's I spatial lag coefficient. [d] spatial lag coefficient. *indicates a 0.1 significance level; **indicates a 0.05 significance level; *** indicates a 0.01 significance level.

As Table 3 shows models, obtained by simple averaging of lead tests for SCAs (Table 3) and by interpolation (Table 4) provide rather poor fits (R^2 =0.079 -0.081, see Table 1 and R^2 =0.066 - 0.077; Table 4). Notably, model fits are higher in VP models (R^2=0.251-0.270; Table 5), indicating that the latter models appear to improve the models' explanatory power, at least compared to the former model runs (see Tables 3-4).

Characteristically, in the VP-based models, the lead exposure variable emerged as statistically significant and exhibits the expected sign, that is, it is *positively* associated with the percent of asthmatic children (B=0.061, P<0.05; see Table 5), while in both SCA-averaged and interpolation-based models (Tables 3-4), the sign of this association is unreasonably negative, implying that lead exposure may have a protective effect on children.

Table 4: Factors affecting the percentage of children with asthma calculated using interpolation based techniques - IDW and Kriging (geographic resolution - SCAs; method -OLS)

Variable	Model 3- Kriging[a]	Model 4- IDW[a]
	B[a]	B[a]
(Constant)	-12.474 (-0.695)	-11.082 (-0.618)
Lead exposure	-0.021 (-1.111)	-0.012 (-1.027)
Obesity	0.045 (0.254)	0.045 (0.267)
Income status	0.082 (1.061)	0.110 (1.392)
Age	2.700 (1.527)	2.485 (1.405)
Number of obs. [b]	72	72
R^2	0.077	0.066
F	1.222	1.190

[a] Regression coefficient and t-statistics in the parentheses; [b] number of valid observations list-wise; [c] Moran's I spatial lag coefficient. [d] spatial lag coefficient. *indicates a 0.1 significance level; **indicates a 0.05 significance level; *** indicates a 0.01 significance level.

Table 5: Factors affecting the percentage of children with asthma (geographic resolution – Voronoi polygons; methods: Ordinary Least Squares (OLS) and Spatial Lag (SL) regressions)

Variable	Model 1-OLS[a]	Model 2-SL[a]
	B[a]	B[a]
(Constant)	-49.756** (-2.626)	-49.694*** (-2.783)
Lead exposure	0.061** (2.367)	0.063*** (2.543)
Obesity	0.233 (0. 785)	0.220 (0.790)
Income status	-0.121 (-0.903)	-0.110 (-0.873)
Age	5.783*** (3.135)	5.836*** (3.358)
Number of obs. [b]	45	45
R^2	0.268	0.270
F	3.655**	
Log likelihood		-147.93
Moran's I [c]	0.461	
Rho[d]		-0.071

Note: a Regression coefficient and t-statistics in the parentheses; b number of valid observations list-wise; c Moran's I spatial lag coefficient. d spatial lag coefficient. *indicates a 0.1 significance level; **indicates a 0.05 significance level; *** indicates a 0.01 significance level.

DISCUSSION

Although the use of VP in environmental and geographic research is not new (Benenson et al., 2002; Benenson and Omer, 2003; Anselin et al., 2005), in previous studies this technique was used mainly for visualization purposes, data comparison, and nearest neighbor queries. However, in empirical studies, there is often a need to analyze the association between several geographically referenced objects while taking into account potential confounders which may affect it. Hence, in the present analysis, we attempted to illustrate the use of VPs for a multivariate analysis, in which the association between soil pollution exposure estimates and asthma morbidity was controlled for socio-economic status of the study population and its health attributes. To the best of our knowledge, the proposed empirical approach of using VPs for generating relatively homogeneous exposure areas for a multivariate statistical analysis is novel, and helps to minimize potential biases arising from exposure misclassification.

The potential usefulness of the proposed approach may be attributed to the fact that in empirical environmental research, there is often a need to combine and analyze data obtained for different resolution levels: group-level data derived from surveys, data obtained from individuals, mixed data from both surveys and individuals, and data for statistical areas whose boundaries are established for purposes other than health investigations (Aherns et al., 2004).

While population level data obtained from e.g., census designated statistical areas, are most readily available, they have several disadvantages. Thus, for instance, these population level data normally provide the researcher with a limited number of variables which rarely go beyond basic demographic attributes and aggregated income counts. Census data do not also include exposure estimates, which normally come from soil tests, measurements provided by air quality monitoring stations (AQMS) or estimated by air dispersion modeling. Since census designated areas, on the one hand, and networks of soil samples and monitoring stations, on the other, do not overlap, the same pollution levels are effectively assigned to all residents of relatively large territorial divisions, within which actual exposure levels may vary considerably. This is likely to lead to an exposure misclassification bias and erroneous estimates of exposure-health effect associations.

The use of various interpolation techniques, such as *splines*, inverse distance weighted method (IDW), kernel smoothing, or *kriging* is one possibility to address this potential bias (Aherns et al., 2004; Kloog et al., 2009). However, these interpolation techniques have several drawbacks, such as a mismatch of results obtained by different interpolation tools and "error propagation" (Wakefield and Shaddick, 2006).

The analytical approach proposed and tested in the present study is relatively simple. In the first step of the analysis, VPs is created around soil sample points. Next, population data are superimposed upon the VPs and averages are computed for each VPs, thus enabling a subsequent multivariate analysis of potential association between soil contamination and population health attributes.

Unlike a commonly used analytical approach based on census designated areas for exposure assessment, VPs polygons, formed around a relatively dense net of soil sample points, are less likely to cause such an exposure misclassification bias thus leading to more accurate assessments of environmental health effects. The present analysis confirms this assumption. While the SCA and interpolation based models did not detect a correct association between lead contamination and children health, such an association was detected in the VP models. This outcome highlights the advantages of using the Voronoi rezoning technique, as opposed to traditional SCA zoning tools.

It should be noted, however, that the use of the VPs technique requires a large amount of observation points (e.g. soil sample points or a dense net of AQMS), around which VPs can be formed. An alternative may be using air pollution grids generated by air dispersion modeling (Wang et al., 2006; Aeromod, 2010), which may serve as proxies for environmental pollutants dispersed with the air and accumulated in soil around the study cohort's residences.

CONCLUSION

As the present study demonstrates, model fits were consistently higher in the Voronoi tessellation models than in the SCA and interpolation models, indicating that, in line with our initial research hypothesis, the VP method does appear to improve the multivariate models' explanatory power. As we suggest, the proposed technique of VP rezoning may be applicable to a wide range of empirical studies which use SCA's that do not fit the "real" exposure zones and may thus cause exposure mis-classification biases and erroneous cause-effect estimates.

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