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Comparing proximity measures of exposure to geostatistical estimates in environmental justice research

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Abstract

This paper tests the validity of proximity as an estimate for environmental health hazard exposure, and suggests how it may be used as an indicator in future environmental health and justice research. Using geostatistics and geographic information systems, air pollution monitoring data in Hamilton, Canada are interpolated to obtain local estimates of total suspended particulates. These estimates are used address the following questions: How does the distribution of proximity to health hazards compare with monitored air pollution data? Does the use of proximity rather than air pollution data significantly change the substantive conclusions of environmental injustice in models with sociodemographic data? The results show that proximity measures can be useful indicators if flexibly applied. Guidelines for future applications are discussed.

Keywords: GIS; Environmental justice; Proximity; Validation; Kriging; Geostatistics

1. Introduction

Although environmental justice research has developed and diversified (Holifield, 2001), cross-sectional studies continue to analyze the extent to which low-income and minority populations are disproportionately exposed to environmental health hazards. Research methodology has become a central issue (Bowen, 2001) as uncertainty surrounds the analytic methods used to model the nature and spatial extent of environmental health hazards and their association with at-risk communities. This is especially true of studies that use spatial metrics to characterize exposures in the absence of environmental monitoring data. The objective of this paper is to test the validity of spatial metrics, particularly proximity, to approximate hazard exposure.

We address this objective with an analysis of air pollution in the City of Hamilton, Canada, which has high-resolution air pollution monitoring data. Hamilton has seen substantial environmental justice research, which provides an excellent frame of reference to test proximity metrics. This paper addresses the following questions: How does the distribution of proximity to health hazards compare with monitored air pollution data? Does the use of proximity rather than air pollution data significantly change the substantive conclusions of environmental injustice in models with sociodemographic data?

2. The need to validate proximity measures

Environmental justice researchers recognized the need to cross-validate exposure assessment methods (McMaster et al., 1997; Sheppard et al., 1999; Harner et al., 2002). Where environmental monitoring data were available, advanced techniques such as plume dispersion modeling and spatial interpolation have been used (Buzzelli et al., 2003; Jerrett et al., 2001; Chakraborty and Armstrong, 2001). However, detailed emission and monitoring data are often unavailable. In addition, various spatial metrics are needed to proxy for ambient health hazards, including: co-location of hazards and disadvantaged communities (Greenberg, 1993);

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Fig. 1. Air monitoring, major roads, and industrial land uses in Hamilton, 1995/1996.

buffering (Glickman, 1994; Chakraborty and Armstrong, 1997; Neumann et al., 1998); and proximity to hazards as an estimate of exposure (Bolin et al., 2002; Cutter et al., 2001; Perlin et al., 2001).

In the absence of environmental monitoring data, a need exists to ensure that spatial metrics adequately characterize exposure and result in the same substantive conclusions (Neumann et al., 1998; Sexton and Adgate, 1999; Bowen and Wells, 2002). The issue is of particular concern because geographic information systems (GIS) can easily facilitate the use of spatial metrics but inappropriate application can bypass sound methodology (Maantay, 2002). At the same time, proxies are flexible and can signal the need for further justice research. Spatial metrics can "…provide a benchmark for further scholarly research, a practical community indicator of environmental justice, and an initial comparison measure between cities" (Harner et al., 2002, 319). Spatial metrics of exposure can in turn lead to the implementation of environmental monitoring, perhaps based on preliminary analyses of inequitable health outcomes (IOM, 1999; Hertzman et al., 1987; Macey et al., 2001; Maantay, 2002).

Testing and validating proximity measures has several advantages over other spatial metrics, in particular the ability to model a continuous hazard field and its potential impact along socioeconomic status (SES) gradients. Methodological concerns in environmental justice research revolve around how best to model exposure to hazards. This results in a second problem of characterizing exposure among target groups. Co-location and buffer analyses are limited because of arbitrary administrative boundaries drawn around at risk communities or arbitrary buffer radii. Hazards are treated as present or absent; the surrounding population as either exposed or unexposed within administrative boundaries, such as census blocks. On the other hand, proximity studies measuring distances between populations of interest and hazard sites are based on a continuous hazard field to characterize potential exposure. Ultimately, if a connection with the health literature is to be made, exposure should be examined along social status gradients, rather than simply for binary presence or absence.[1]

The following approach tests proximity against a reliable frame of reference—monitored air pollution data for the City of Hamilton, Ontario (Fig. 1). Prior environmental justice research in Hamilton (Jerrett et al., 2001; Buzzelli et al., 2003) is compared to the proximity method developed by Cutter et al. (2001): cumulative proximal exposure (CPE). Bolin et al. (2002) have presented an equivalent method to integrate different hazards (e.g., toxic emissions and traffic pollutants). CPE has a strong basis in the geographical literature on spatial externalities, in particular the distance decay function. It can also integrate several hazards without reference to expensive monitoring data. For Hamilton, monitored ambient total suspended particulates (TSP) are available from the Ontario Ministry of the Environment (MOE). These data are spatially interpolated for localized values and compared with CPE to land uses emitting this air pollutant: industrial and transportation sources. Comparisons are made

[1] This is the approach taken in the population health literature which his explicitly concerned with social status gradients. This would seem to be a useful conceptual way forward for the environmental justice literature to make a health connection.

directly between TSP and CPE, and indirectly in their associations with variables representing SES and race, as would be done in a full environmental justice analysis.

3. Data and methods

Arc View 3.2 GIS (ESRI Corp, Redlands, CA) is used to integrate TSP, proximity measures, and census data at the census tract level of aggregation within Hamilton. The relationship between TSP and proximity are examined, and building directly on prior environmental justice research for Hamilton, both are regressed on sociodemographic variables from the 1996 census.

3.1. TSP interpolation

TSP particles range up to 50 microns (μm) in aerodynamic diameter. Fine particles (up to 2.5 μm, $PM_{2.5}$) have been most closely associated with significant health effects including lung cancer and cardiopulmonary mortality (Krewski et al., 2000; Pope et al., 2002), although earlier research also found associations between health effects and PM_{10} or TSP. A recent study in Hamilton reported significant health effects associated with TSP, including cardiopulmonary and all cause mortality (Burra et al., 2002). In Hamilton, TSP is typically composed of aerosols and metals originating from combustion and industrial processes, including sulphur, nitrogen compounds, lead, and carbon. Local emissions are heavily influenced by the central city's heavy steel fabrication complex that can emit up to one-third of all local TSP, anchoring this pollutant's distribution. For these reasons, Hamilton has been the basis of substantial environmental justice and health research and is therefore a good frame of reference for validating CPE.[2]

Local estimates of ambient TSP levels were obtained by spatially interpolating Hamilton's air monitoring network. TSP was measured in the standard $\mu g\,m^{-3}$, at 20 stations located throughout the city in 1995 (Fig. 1).[3] The year 1995 is closest to the census of 1996 for which we have a large number of stations to allow for spatial interpolation; government funding cutbacks had reduced the network to only 13 stations in 1996. In contrast to PM_{10}, for example, TSP tends to show a more punctuated distribution because of its large fraction size and short-range transport, even within an urban region.

Small-area spatial variability in TSP necessitates an interpolation technique that takes into account local and global trends in the spatial process. Universal kriging was chosen after having tested alternative interpolators (see Jerrett et al., 2001 and Buzzelli et al., 2003 for details of interpolator selection). Universal kriging is appropriate when trends (spatial dependence) are present in a spatial process (Burrough and McDonnell, 2000), a feature of TSP found in earlier research on Hamilton (Farhang, 1983; Pengelly et al., 1984; Jerrett et al., 2001). Universal kriging also preserves the original data units while simultaneously estimating global and local TSP levels (TSP in geometric means). Estimates were assigned to census tract centroids weighted by residential land use in S-Plus 6 software using the point kriging technique. The kriged surface is shown in Fig. 2.[4]

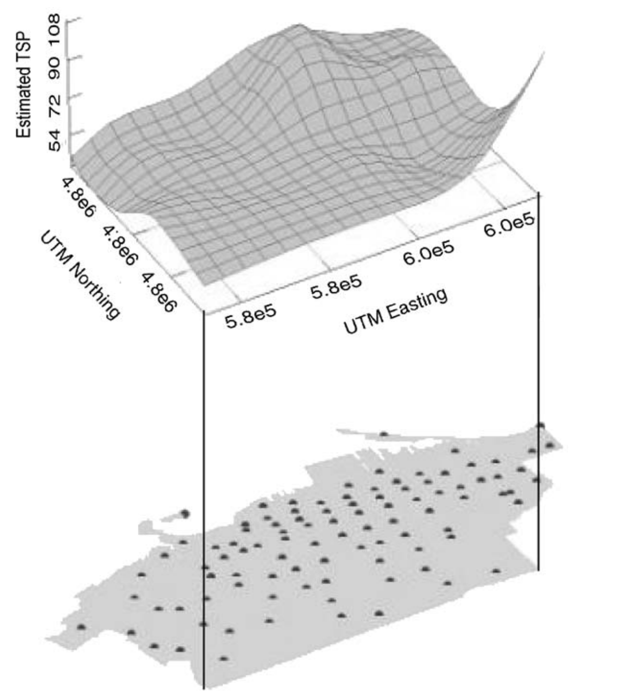

Fig. 2. Kriged estimates of TSP in Hamilton, 1995.

While Hamilton's network is extensive compared to other intra-urban monitoring in other places, the number and distribution of stations necessitated sensitivity analyses. The first test looked at the similarity of the estimated surface with that of earlier years, including years with more monitoring stations and less suburban sparseness. The 1985 (34) and 1990 (23) stations estimated census tract values correlated at $r = 0.93$, while the 1995 stations correlated with these two earlier years at $r = 0.71$. Earlier research suggested a systematic temporal change in the distribution of TSP, due in part to a spatial restructuring of industrial activity (Buzzelli et al., 2003). A comparison with an estimated surface for

[2] We originally intended to use other pollutants, but these are not monitored at a sufficient number of locations for the period of this study to make for a reliable test of proximity.

[3] Fig. 1 displays 18 stations. Two are located just west of the map extent.

[4] For a complete discussion of the alternative interpolators explored, see Buzzelli et al. (2003).

Table 1
Descriptives of health hazard exposures

	Mean	Standard deviation	Minimum	Maximum	Range
Kriged TSP (total suspended particulates)	55.28	8.09	39.33	87.63	48.30
CPE 1 mile (land use)	4.01	5.55	0.00	18.94	18.94
CPE 1 mile (major roads)	2.55	2.25	0.00	8.44	8.44
CPE 1 mile (total)	6.56	5.45	0.00	22.00	22.00
CPE 5 miles (land use)	54.06	24.29	7.47	92.02	84.55
CPE 5 miles (major roads)	54.49	10.61	23.98	70.34	46.36
CPE 5 miles (total)	108.56	24.71	48.18	141.48	93.30
CPE maximum distance (land use)	111.03	16.58	70.44	133.26	62.81
CPE maximum distance (major roads)	132.78	9.96	103.19	146.10	42.91
CPE maximum distance (total)	243.82	22.87	173.63	270.74	97.11

Note: CPE stands for cumulative proximal exposure, and represents an inverse distance weighting from all hazard locations to each point of interest (in this case census tract centroids). All distances are in cumulative meters, as specified in Formula (1).

1994 (same 20 stations) corroborates this, correlating at $r = 0.85$. A more variable surface in 1995 would appear to reflect the TSP distribution, rather than sparseness in the monitoring network. Another sensitivity analysis cross-validated the internal validity of the 1995 kriging approach by successively removing each air monitoring station from the kriging estimation and producing a new surface in its absence, for a set of twenty new surfaces. The estimates were then compared with (1) the original monitored TSP values and (2) the estimated values used in the analysis, as derived from the full set of monitors. Correlations for the former did not fall below $r = 0.93$; most equaled or exceeded $r = 0.98$. Similar results were obtained in comparisons with the estimates from the full network. Visualization of the new cross-validation surfaces also showed they largely resembled that of the complete set of monitoring stations in 1995. These sensitivity analyses suggest that the 1995 surface accurately represents the spatial process of TSP distribution and thus provide a good frame of reference for testing the validity of distance as an exposure proxy.[5] Table 1 displays the descriptive statistics for TSP estimates.

3.2. Proximity measures

To test proximity against geostatistical TSP estimates, the same census tract centroids were used in combination with a new set of spatial data, specifically locational data of major roads and heavy manufacturing facilities—the principal anthropogenic generators of ambient particles (Health Canada, 1998).[6] Road network data were drawn from a comprehensive and topologically integrated geo-database for Canada developed by DMTI Spatial Inc. (Markham, Ontario, Canada). This geo-database includes road coverages (i.e., arcs and vertices) and urban land uses. Several roadway arcs were removed from the database, as they had not yet been completed or constructed by 1996 (primarily along the Lincoln Alexander Expressway in the suburbs, then in the planning stages).[7] In other cases, roadway arcs lacked representative segments, and these were added while some very short arcs contained several segments that had to be simplified. To simplify the distance measures, all segments were generalized such that none was closer than 200 m to each other. A total of 210 segments were used to compute distances with census tract centroids.[8] This included roadways up to 1 mile (1609 m) beyond the city limit. In addition, a buffer incorporated trans-boundary pollution from traffic just beyond the edge of the city.

DMTI data were also used to measure distances from point-source manufacturing facilities. DMTI data identify land parcels zoned as industrial, though zoning does not necessarily equate with active industrial activity, or with TSP emissions. DMTI data were therefore validated in two steps. First, many of the small land parcels zoned 'industrial' in the DMTI database were 'ground truthed' to determine if they in fact could be sources of TSP. Several parcels not found in the city's main

[5] For an analysis of conditions under which kriging should not be applied see Le et al. (2001).

[6] Minor roads are not considered major urban regional contributors to TSP levels. They are also ubiquitous and unlikely to result in inequitable exposures.

[7] Due to a deep and long-lasting recession, Hamilton, much like the rest of Ontario, saw little development during the first half of the 1990s. Right-of-ways for roadways such as the "LINC" idly waited the boom years of the latter 1990s for construction and use.

[8] Use of more standard line generalization algorithms did not produce satisfactory results: either too many segments were removed from long arcs which became over generalized and too many remained along shorter road segments, or, too few were removed altogether resulting in little change. The former case resulted in crude generalizations of otherwise long and sinuous links while the latter did little to change the road network and attendant vertices. Buffering maintained a representative number of segments and was amenable to the cumulative distance measurements needed for the analysis. Several buffer distances were explored before the 200-m distance was finally implemented.

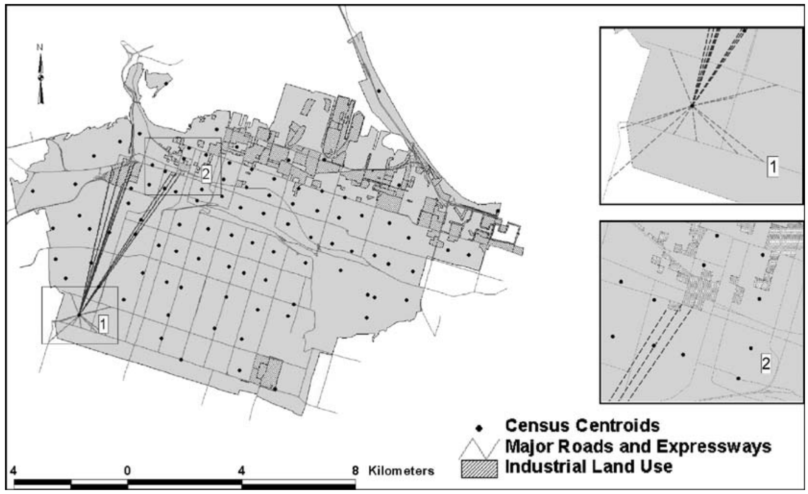

Fig. 3. CPE to major roads and industrial land uses, Hamilton, 1995/1996.

industrial zones (mainly downtown, but also central western, and suburban eastern) but found in the mid-central part of the city, were also excluded. Second, the Ontario MOE's data from the National Pollutant Release Inventory (NPRI) helped to corroborate that most industrial sources were located in the northeast heavy manufacturing core. Taken together, these procedures confirmed the location of 168 land parcels as industrial TSP point-source emitters in Hamilton, again including a buffer to include facilities up to 1 mile beyond the municipal boundary.

With roads and industrial facilities identified, distance measures were then taken between census tract centroids and these features, specifically road buffer centroids and the edges of industrial land parcels.[9] Using several variants, distance measures followed the CPE method developed by Cutter et al. (2001):

$$\mathrm{CPE} = \sum_{j}^{\#\text{emission points}} \left(1.0 - \frac{d_{ij}^{e}}{T_j^{e}}\right), \qquad (1)$$

where CPE is therefore the inverse weight of the cumulative distance, d_{ij}, between each census tract centroid, i, and all emission points, j; e is the rate of reduction in exposure; T_j, is the distance at which exposure from facility j is considered negligible. Fig. 3 displays CPE as applied to one residential land use weighted centroid, for its ten nearest road and industrial land use neighbors. Descriptive statistics comparing TSP and CPE are shown in Table 1.

The form of the CPE model is flexible enough to incorporate qualitative information about the nature and extent of spatial processes. The rate of reduction in exposure, e, may be varied to emulate a non-linear distance decay function that can accommodate local climate and topographic functions. As Cutter et al. (2001) reported, it is not always clear which type of non-linear function is most appropriate. To cross-validate the usefulness and demonstrate the flexibility of CPE in this case, e is modified such that CPE resembles the regional distribution of TSP. The CPE may also be adjusted by varying T to reflect assumptions made about the distance at which exposure becomes negligible. Cutter et al. (2001) used distance bands from 1 to 5 miles. In this case, each of these was chosen in addition to the maximal distance separating i and j, for an overall regional view: T was set to 1 mile (1609 m), 5 miles (8047 m) and the maximum distance separating i and j (17,471 m for roadways; 17,068 m for industrial land parcels) across the region (see Table 1).[10]

3.3. Statistical tests

Correlation and bivariate regression models are presented for the TSP and CPE variables. CPE is tested against TSP for both land use types and each distance interval; that is, for both roadways and heavy manufacturing land uses, each at 1 mile, 5 miles, and the longest distance separating these and census tract centroids. TSP is treated as a function of CPE in a series of bivariate linear regressions and a visualization of curves fit with the various CPEs using different functional forms. Testing against TSP in this manner allows us to determine which land uses, and at what distances, we can rely on proximity to proxy for ambient TSP levels.

[9] Use of industrial land parcel centroids produce the same statistical results in the end, by merely introducing a systematic difference in the distance measurements. Parcel edges are used here because they reflect the true configuration of this land use, on 'the ground', in the city.

[10] Cutter et al. (2001) used imperial measures that are commonly applied in the justice literature, and correspond to guidelines suggested by the US EPA. Miles are therefore used here but equivalent meter distances are also given.

A final test compares CPE with TSP in regression models involving SES variables. The census variables used here have been found to be statistically significant in earlier justice research in Hamilton (Buzzelli et al., 2003). CPE at the various distance bands and land uses are substituted for TSP estimates to determine if substantive conclusions are significantly altered by use of proximity versus monitored air pollution data.

4. Results

Fig. 4 shows the CPE surfaces for major roads and industrial land uses at each distance interval. The surfaces show the same general trend as the TSP surface in Fig. 2 in terms of a central peak and general decline toward the suburbs. The 1-mile CPE contains the most local variability and gives the greatest weighting to the industrial core. At this short distance, proximity to Hamilton's heavy manufacturing complex appears to be important and suggests that CPE and TSP are closely correlated. At 5 miles and the maximum regional extent, the surfaces are nearly identical to each other and do indicate a weighting toward the city's industrial core but they are much less variable, descending monotonically toward the suburbs. We would expect a positive through less direct association with TSP in these cases due to the higher contribution from traffic sources.

Table 2 displays correlations between TSP and the various CPE measures; roadways, industrial land uses, and both together: each at the 1-mile, 5-mile, and full regional distances. Whereas correlations between TSP and roadways are weak (either positive or negative) correlations, the correlations are quite high and significant for industrial land use. In terms of proximity, however, correlations do not change significantly. Correlations between both land use types and TSP at all distances are driven by the CPE of industrial land use.

These correlations suggest that proximity measures may be more reliable where point source air pollution emissions are spatially clustered. The importance of Hamilton's agglomerated steel fabrication complex to regional TSP levels results in a much higher correlation between TSP and the CPE of industrial land use. The presence of major roadways throughout the region, versus the concentration of industrial land uses, appears to reduce any regional disparities. If this is true, then TSP distribution should be a function of distance from its sources. This distance decay assumption underlies much justice and environmental health research. In bivariate regressions, however, R_a^2 are weak at best. The strongest association is found for the CPE of industrial land uses at the 5-mile distance band and the full regional extent, as well as the 1-mile band for industrial land uses and roadways combined ($R_a^2 \sim 0.22 - 0.24$).

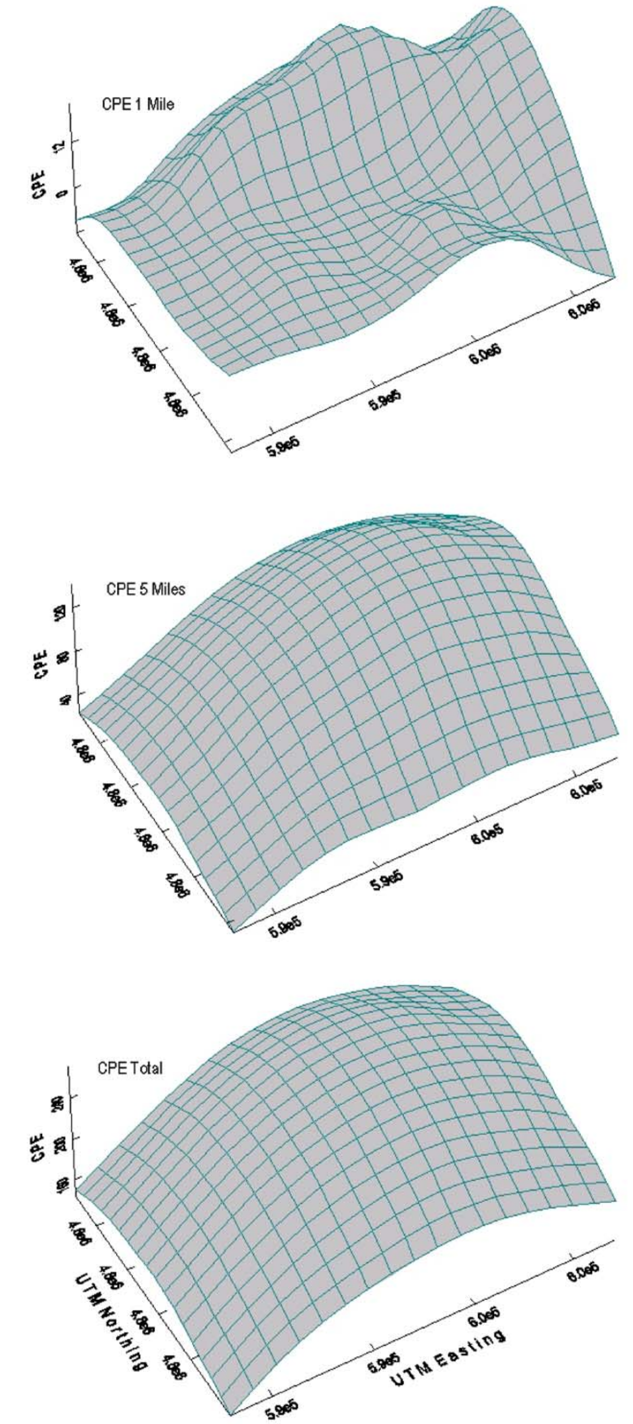

Fig. 4. CPE surfaces for combined land uses at three distance bands.

Scatter diagrams and curve-fitting reveal that poor linear regression results are due to non-linear relationships between TSP and CPE, especially at the 5-mile and full regional distances. At 1 mile, the bivariate distribution of TSP and CPE among Hamilton's census tracts is linear (though weak). At greater distances, a quadratic function in particular produces a much better fit since the bivariate distribution is exponential in form. The

Table 2
Correlations of TSP and CPE

	TSP	CPE 1 mile (land use)	CPE 1 mile (major roads)	CPE 1 mile (total)	CPE 5 miles (land use)	CPE 5 miles (major roads)	CPE 5 miles (total)	CPE maximum distance (land use)	CPE maximum distance (major roads)	CPE maximum distance (total)
Kriged TSP	1.00	0.31[a]	−0.02	0.45[a]	0.50[a]	−0.17	0.42[a]	0.47[a]	0.14	0.40[a]
CPE 1 mile (land use)		1.00	−0.08	0.93[a]	0.43[a]	−0.52[a]	0.21	0.38[a]	−0.11	0.21
CPE 1 mile (major roads)			1.00	0.22[b]	−0.41[a]	0.26[b]	−0.30[a]	−0.36[a]	−0.09	−0.30
CPE 1 mile (total)				1.00	0.39[a]	−0.44[a]	0.19	0.34[a]	−0.19	0.17
CPE 5 miles (land use)					1.00	−0.18	0.91[a]	0.97[a]	0.30[a]	0.83[a]
CPE 5 miles (major roads)						1.00	0.25[b]	−0.01	0.78[a]	0.33[a]
CPE 5 miles (total)							1.00	0.95[a]	0.63[a]	0.96[a]
CPE maximum distance (land use)								1.00	0.45[a]	0.92[a]
CPE maximum distance (major roads)									1.00	0.76[a]
CPE maximum distance (total)										1.00

Note: For a definition of CPE, see Table 1.
[a] Significant at $p<0.01$.
[b] Significant at $p<0.02$.

linear relationship at the 1 mile distance, together with the exponential relationships beyond that, suggest that the standard CPE model can be modified for better local and regional representation. To adjust for the negative skew and linearize the relationship between TSP and CPE, greater weight was applied to shorter distances. This was done by modifying the CPE model thus:

$$\mathrm{CPE} = \sum_{j}^{\#\text{emission points}} \left(\frac{d_{ij}}{T_j}\right)^{-e}. \qquad (2)$$

By taking the negative reciprocal exponent of the rate of reduction of the distances, inverse distance weighting is inherently applied and the order of distances is maintained (i.e., there is no need to take the inverse of the distance values, as in the original formula). The negative reciprocal transformation applies relatively more weight to the shorter distances in the spatial system. Those performing best had the desired effect of raising the goodness of fit between TSP and CPE. For industrial land uses alone, the change was minor. But for both land uses combined, modification of e (-8 and -9) brought substantial improvements, especially at the maximum regional distance where R_a^2 rose from 0.15 to 0.42.

Finally, the effect of redefining e was tested for associations with SES variables found to be significant with TSP in prior research (Buzzelli et al., 2003). Specifically, dwelling value has been the most consistent 'predictor' of the variation in TSP; its negative correlation is shown in Table 3. The proportion of Latin-American population is also significantly positive. With the TSP model as a frame of reference, we may gauge the performance of both the standard CPE model and the variation introduced here. Table 3 shows that both covariates in all CPE models take the same sign as in the TSP model, though statistical significance of the Latin-American variable is lost with the standard CPE method. Although model fit could vary given that TSP is not a simple function of CPE, the substantive conclusions that may be reached by informed use of CPE appear to be consistent with those derived from geostatistical modeling of monitored air pollution data. Notwithstanding expected variation in overall model fit, given that TSP is not a simple function CPE (in any form), the substantive conclusions that may be reached by informed use of CPE appear to be consistent with those derived from geostatistical modeling of monitored air pollution data.

5. Discussion and conclusions

The performance of CPE suggests that distance measures are a reliable proxy for health hazard exposure. Although CPE and any other proximity measure can be computationally demanding, they are

Table 3
Comparisons of multiple associations between TSP, proximity, socioeconomic status, and race

	Intercept	Average dwelling value	% Latin-American population	Model fit: adj. *R sq.*
TSP model[a]	4.23 ($t = 74.45$)	−1.97E−06 ($t = -4.97$)	3.54E−02 ($t = 3.28$)	0.30 ($p = <0.01$)
CPE at 5 miles (standard)	168.12 ($t = 16.28$)	−4.43E−04 ($t = -6.15$)	0.17 ($t = 0.085$)	0.26 ($p = <0.01$)
CPE at 5 miles (modified *e*)	789.25 ($t = 11.00$)	−1.96E-03 ($t = -3.91$)	40.72 ($t = 2.99$)	0.22 ($p = <0.01$)
CPE at full regional extent (standard)	293.02 ($t = 29.89$)	−3.74E−04 ($t = -5.47$)	1.42 ($t = 0.77$)	0.25 ($p = <0.01$)
CPE at full regional extent (modified *e*)	1634.63 ($t = 22.81$)	−3.65E-03 ($t = -7.13$)	33.26 ($t = 2.39$)	0.40 ($p = <0.01$)

[a] Transformation of TSP to approximate the Gaussian distribution results in better model fit.

sufficiently flexible and inexpensive to explore environmental justice hypotheses. If proximity measures demonstrate the potential for injustice, this may indicate a need for more expensive monitoring or dispersion studies. The results show that manipulation of the CPE makes it a flexible technique for preliminary environmental justice research, in much the same way that buffer analyses have been used (Harner et al., 2002), but with the advantages of continuous exposure and social status gradients as well as capacity to integrate multiple hazards.

In presenting the CPE model, Cutter et al. (2001) recognize the simplifying assumptions that go with using a spatial metric for exposure, beyond those implicated in air pollution hazards. Awareness of local circumstances can improve the applicability of distance measures. In this case, the distribution of TSP in Hamilton served as a frame of reference for testing the applicability of CPE. In fact, an estimated TSP surface and monitoring network is unnecessary to make this kind of qualitative judgment. The land uses of interest, and the CPE model, can be calibrated based on local knowledge of the distribution of pollutants to produce reasonable proxies for health hazard distribution. Local knowledge of the influence of heavy industry provides enough qualitative information to weigh these land uses and produce favorable results.

Having said that, how does one apply proximity as the metric of exposure without the benefit of an air monitoring network or other extraneous information? Proximity may be weighted by quantity and toxicity of hazards and these qualitative adjustments add further to the sophistication of proximity as an indicator (Bowen et al., 1995; Neumann et al., 1998; Cutter et al., 2001). For instance, should the focus be a particular 'at risk' community (Chakraborty and Armstrong, 2001) where hazards may be weighted according to the level of risk they pose? Perhaps what is needed is a host of supplemental tools such as community risk assessment (NRC, 1983). This could explore the need for more expensive approaches such as Community Risk Assessments (NRC, 1983). In addition, the relative weighting of communities across space permit the inclusion of two or more hazards such that a composite picture of environmental justice is possible (Bolin et al., 2002).

Finally, a middle ground may also be attainable. Although an extensive air-monitoring network is needed for spatial interpolation of TSP, only a few stations are necessary to calibrate a CPE surface or to cross-validate its correlations with real monitoring data. Perhaps the principal insight from these observations is that any proxy for environmental health hazard exposure should be applied flexibly. Alternative exposure metrics should be reported, and they should inform substantive conclusions about the validity of the measure in different applications.

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