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GIS-based measures of environmental equity: Exploring their sensitivity and significance

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In order to determine whether principles of environmental justice have been violated, a large number of empirical studies have been carried out to ascertain whether minority and low-income populations are disproportionately exposed to industrial pollution. This study provides a comparative evaluation of two commonly employed proximity measures in GIS-based environmental equity assessment, examining their influence on the results of the analysis, and proposes a methodology for evaluating the significance of these results. 1990 census data on population characteristics and data from the 1995 EPA's toxic release inventory (TRI) for the City of Minneapolis, MN are used. These results also allow a preliminary assessment of environmental equity/inequity in potential exposure to airborne toxic chemicals for racial minorities, poor people and children in Minneapolis. In the third part of the paper we develop and employ a geographic randomization methodology for assessing the significance of these results.

Keywords: *environmental justice, risk assessment.*

Introduction

In 1987 the United Church of Christ published a landmark report, based on a nationwide analysis, documenting the proximity of communities of color to toxic waste (UCC-CRJ, 1987). This study and numerous other highly publicized activities of the environmental justice movement have galvanized a national debate about the extent to which poor and communities of color are disproportionally exposed to toxic hazards, about reasons for this, and possible remedial measures. Federal government responses to this debate included the passage of Executive Order 12898 by President Clinton in 1994 that requires all federal agencies to adopt the principle of environmental justice in programmatic decisions. The federal Environmental Protection Agency (EPA) has instituted a special office on Environmental Justice to oversee compliance with the executive order.

In order to determine whether principles of environmental justice have been violated, a large number of empirical studies have been carried out to ascertain whether minority and low-income populations are disproportionately exposed to industrial pollution. Typically, studies of environmental justice, focusing on the inequalities in exposure to toxic hazards among subpopulations, are cast within the tradition of distributive justice, addressing equity of outcomes. [1] As a result, such studies are often referred to as environmental equity analysis.

Studies of environmental equity are inherently spatial in nature: Debates have to do with who lives how far from toxic hazards, and why those hazards and communities are located where they are. Thus any analysis of environmental equity or inequity requires selection of a spatial methodology that measures as precisely as possible degrees of inequity in exposure among different subpopulations. During the past decade geographic information systems (GIS) software has increasingly been utilized in environmental equity analysis. This is because GIS allows for (1) the integration of the different data sources that are necessary for such analysis, such as data on locations of hazardous sites (e.g., toxic release inventory (TRI) sites, Petrofund, Superfund sites), and population characteristics (e.g., race, income, age); (2) the application of spatial analytic techniques (including overlays and buffering); (3) the potential integration of spatial models of potential exposure, such as plume dispersion models; and (4) the visual representation of complex data, normally in cartographic format.

The purpose of this paper is twofold: to undertake a comparative evaluation of two commonly employed proximity measures in GIS-based environmental equity assess-

1. Abbreviations: CBD, central business district; GIS, geographic information system; TRI, toxic release inventory

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[1] Justice is a very broad concept. Crudely speaking two conceptions of justice can be identified (Young, 1990; Smith, 1994): Distributive justice, referring to the equity in distribution of benefits and burdens, and procedural justice, referring to equitable procedures through which justice is to be achieved, a process where all have an equally effective voice.

ment, examining their influence on the results of the analysis; and to propose a methodology for evaluating the significance of these results. 1990 census data on population characteristics and data from the 1995 EPA's TRI for the city of Minneapolis, Minnesota are used as a case study. Although one might argue that these two data sets are not compatible because of shifting demographics, they represent the best available sources of information. We start with a brief discussion of different GIS-based methodologies utilized in environmental equity studies, assessing the progress to date and methodological problems that remain. This is followed by a description and sensitivity analysis of the two most commonly used measures of proximity employed in GIS-based environmental equity analyses, applied to the city of Minneapolis. These results also allow a preliminary assessment of environmental equity/inequity in potential exposure to airborne toxic chemicals for racial minorities, poor people and children in Minneapolis. In the third part of the paper we develop and employ a geographic randomization methodology for assessing the significance of these results.

Methodological issues in environmental equity analysis

GIS technology has been used to combine layers of geographic information on environmental hazards and population characteristics in order to analyze the geographic proximity between population characteristics and pollution sources at different spatial scales and represent them graphically in map form (McMaster, 1990; Burke, 1993; Glickman, 1994; Sui and Giardino, 1995; Cutter et al., 1996; McMaster et al., 1997). The most common approach estimates and compares the characteristics of the population in enumeration units (e.g., census tracts, block-groups) that contain environmental hazards (e.g., industrial toxic emissions, toxic waste sites) with characteristics of the population in enumeration units which do not contain such environmental hazards. Alternatively GIS allows for the computation of simple circular buffers at varying distances around hazardous sites, or zonal calculations along major highways (see Figure 3). This type of analysis has been used to calculate differences in population characteristics within and outside buffers and zones in order to ascertain whether vulnerable populations are disproportionately located within buffers and zones close to hazardous sites and routes (Glickman, 1994; Glickman and Hersh, 1995; Sui and Giardino, 1995).

Such simple proximity measures of course do not rigorously account for how potential exposure depends on the direction and the nature of distance decay of the diffusion of toxic chemicals released in the atmosphere. The application of plume dispersion models within GIS is an attempt to account for the directional bias of physical diffusion processes. Geographic plume analysis typically integrates the toxicological characteristics of the chemicals emitted or stored, physical characteristics of the sites, and atmospheric conditions to identify the geographic area and population that is affected by a plume (for an application, see Chakraborty and Armstrong, 1997). Such models frequently also entail simplifying assumptions, for example about average wind direction in an area and about topography, often assumed to be flat, which can lead to erroneous results. Plume models are also much more time consuming to apply, and it may be that under certain circumstances reasonable approximations can be gained from the use of the above described simpler GIS functions, such as overlays or buffering. For any particular place, sensitivity analyses can determine whether geometric approximations are close enough to accurately specified physical diffusion models, at desired levels of data resolution, to act as less labor and time intensive substitutes.

GIS-based proximity analysis has also been combined with various correlation and multiple regression analyses in order to assess the degree and significance of the relationship between hazardous sites/areas and geodemographic characteristics, and to attempt to explain reasons for inequitable distributions (Bowen et al., 1995; Sui and Giardino, 1995; Cutter and Solecki, 1996). These studies suffer from several limitations and specification problems, however (McMaster et al., 1997).

These and other environmental equity studies have rendered different results, revealing associations between population characteristics and exposure to toxic releases which often conflict with one another. Findings range from strong associations suggesting that racial minorities and economically disadvantaged populations are disproportionately exposed to toxic chemicals, to those observing no associations between hazardous sites and minority or poor people, to results suggesting that white and higher income communities rather than poor communities of color disproportionately face potential exposure to toxic releases (for a summary analysis of these findings, see McMaster et al., 1997). A close examination of these studies reveals that these very different results are at least in part a consequence of differences in data used and measures of potential exposure, applied to different kinds of places, at different geographic scales, with data of different levels of spatial resolution. [2]

In spatial analysis of environmental equity, it has now become clear that the choice of the geographic scale of the study area (e.g., states, metropolitan areas, counties, municipalities) and the spatial resolution of data within that

[2] For a detailed discussion of differences in the geodemographic and hazard data used in environmental equity studies and the problems, see McMaster et al., 1997.

study area (e.g., zip codes, census tracts, block-groups) employed, influence the results of the analysis. The environmental equity study of Cutter et al. (1996) for the state of South Carolina demonstrates the influence of spatial data resolution. Using census-tract data, no statistically significant association was found between the location of racial minorities or economically disadvantaged persons and toxic facilities, while county-level data showed a positive correlation between more urbanized, white, middle-income counties and hazardous waste/toxic facilities. The environmental equity analysis of Glickman (1994) in the Pittsburgh area showed that as the resolution was changed from block-groups to tracts to zip codes, the minority population became more important in explaining changes in the number of TRI sites, and per capita income and population density became less significant. Coarse spatial resolution data often do not allow for an accurate assessment of the differential potential exposure of different subpopulations, because of the heterogeneity of the population within these enumeration units. This problem can be addressed by using fine spatial resolution data, such as block-groups and blocks, which are available in digital form since 1990.

For the Twin Cities, McMaster et al. (1997) have shown the influence of scale. At the county scale a stronger relationship between persons of color and TRI sites was identified, whereas at the scale of the city of Minneapolis, a stronger income-based rather than race-based pattern of inequity was observable. The equity analysis of Bowen et al. (1995) for the state of Ohio and the Cleveland metropolitan area shows similar contrasting results. At the state scale, they find a high positive correlation between minorities and toxic sites and release volumes, whereas at the metropolitan scale minority densities and toxic release are inversely related, and there was evidence of income-based inequity.

Differences in findings also arise from different measurements of potential exposure. Most environmental equity studies treat the simple existence of a hazardous site as a surrogate for potential exposure; ignoring important differences in the toxicity of chemicals and the spatial diffusion of toxic releases. Geographic studies incorporating information on the toxicity of emissions have shown significantly different hazardous landscape surfaces and inequities (Bowen et al., 1995; Cutter and Solecki, 1996; McMaster et al., 1997).

Results of environmental equity analysis are also sensitive to the shape and size of buffers, and the method used to delineate the buffer (see Sui and Giardino, 1995; Chakraborty and Armstrong, 1997). For example, Chakraborty and Armstrong (1997, p. 145), using 1990 block group census data and 1994 TRI data for De Moines, Iowa, found that in comparison to circular buffer analysis, plume buffer analysis shows a higher proportion of racial minorities and individuals below the poverty line residing within the buffer area surrounding TRI locations.

The above discussion has highlighted the sensitivity of findings in environmental equity analysis to scale, data resolution, and exposure measures. While a single spatial resolution, scale or exposure measure is neither practicable nor desirable, researchers need to pay attention to and try to resolve these methodological issues in order to minimize error in estimates of inequity and improve the reliability of environmental equity studies.

GIS-based proximity measures: spatial coincidence and buffering

The two most commonly used measures of proximity analysis in GIS-based environmental equity assessment are ‘spatial coincidence’ and analytical buffering. In its most rudimentary form, it is becoming common to examine the association between TRI sites and minority/poor populations using the simple spatial coincidence of the two based on various levels of census data resolution such as tracts, block-groups, or even blocks. In this case, proximate populations are defined as those residing in the census enumeration unit containing a TRI site. A second strategy measures this same association through the application of a GIS-based buffer analysis, in which proximate populations are defined as those living within a predefined distance from a TRI site. Because of uncertainty about how to select this distance parameter, we will experiment here with different buffer distances, i.e., 100, 500 and 1000 yard buffers.

Figure 1 presents these two primary methods for calculating environmental inequity. For this example a set of block groups for the City of Minneapolis and their associated poverty rates (percent below poverty represented as numbers) are used. In the case of the simple measure of spatial coincidence–population and TRI site in the same block group—the value for the block group (darkest shade) containing the TRI site (26%) is used. For the buffer method, all block groups overlapping with the calculated buffer are captured, and the area contained within the buffer is computed. Using this method, the value of 26% would be lowered, since the surrounding block-groups contributing to the buffer estimate all have lower values—17%, 23%, 15%, 19%, 15%, and 24%. The exact method for computing the actual contribution of each block-group to the buffer estimate—based on the percentage of the area contained within the buffer—is explained below.

Research into questions of environmental equity and racism typically focuses on the question of whether people of color, or those in poverty, are more likely to be located close to TRI sites, and we follow this approach here. Because there exist complex relationships between race, ethnicity and poverty that should be part of the analysis,

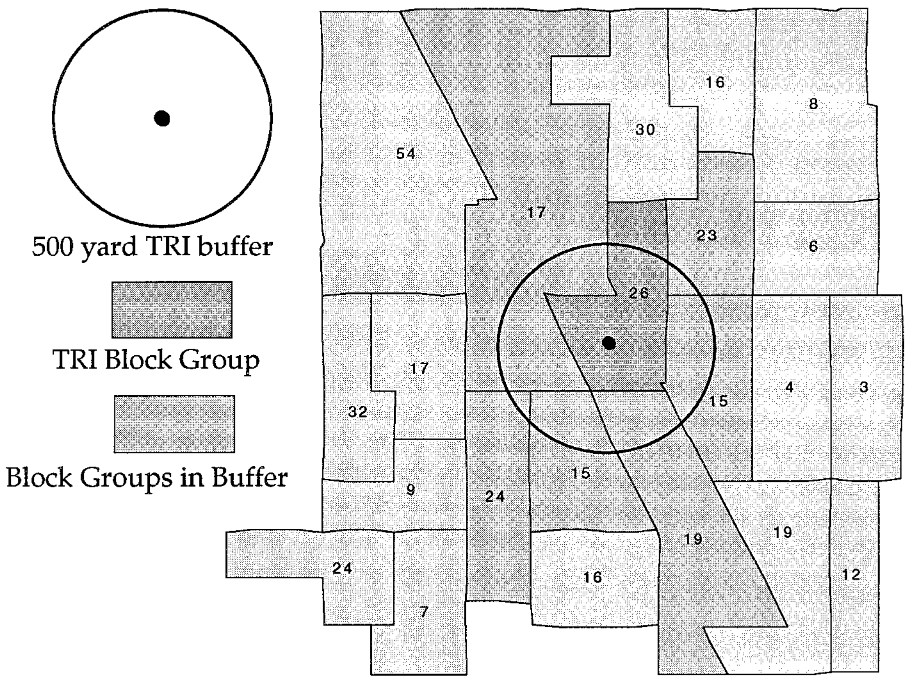

Figure 1. Two measures of proximity: spatial coincidence and buffering.

however, we focus on the poverty characteristics of the five most important racial groups in Minneapolis: Whites, African Americans, American Indians, Hispanics, and Asian Americans, and examine those defined by the US census as living below the poverty level in 1990. In addition, we include information on children less than five years old of all races, because this is a particularly vulnerable population sub-group. The seven variables used are:

- Total White population below poverty
- Total African American population below poverty
- Total American Indian population below poverty
- Total Asian population below poverty
- Total Hispanic population below poverty
- Total Below Five population below poverty
- Total population below poverty

Data for all these variables are available at the block group level of resolution, which forms the basis for this analysis. For each group, we examine the question of whether locations close to TRI sites contain a greater proportion of people in poverty than more distant locations. The basic problem is how, exactly, researchers can establish the existence—and more importantly the strength—of spatial associations between certain geodemographic characteristics of the population and a given source of an airborne toxic release, in this case TRI sites.

The City of Minneapolis, with a 1990 population of 368,000, represents a reasonable mid-size city for such an equity study. Although Minneapolis has a relatively low minority population—one of the lowest among the largest 25 US cities—its minorities are highly segregated. For example, Figure 2, depicting the percentage of African Americans by block group in Minneapolis, illustrates concentration in two clusters—south and northwest of the central business district (CBD). The existence of strong segregation patterns provides a good test case for examining the association between race, poverty and proximity to TRI sites. Finally, access to rich sources of environmental data from the city, including the location of TRI, Superfund, Petrofund, Land Recycling sites as well as pollution permit holders, allow us, in research not reported here, to expand consideration beyond the somewhat problematic TRI database (McMaster et al., 1997).

Method 1: Spatial Coincidence

Figure 2 illustrates the location of block groups in the City of Minneapolis that contain a TRI site. Note the clustering of TRI sites in the northeast sector of the city, east of the Mississippi and north of the CBD, in an area developed for industrial activity many decades ago, as well as a secondary concentration of TRI sites west of the Mississippi River and north of the CBD. Table 1 shows the percentage of the population below the poverty level (or the poverty rate) for Whites, African Americans, American Indians, Asians, Hispanics, children younger than 5, and the total population, residing within and outside TRI-block groups. It should be noted that the Bureau of the Census adjusts the poverty level based on family size. TRI block groups (TRIBG, Table 1) are block groups that contain at least one TRI site.

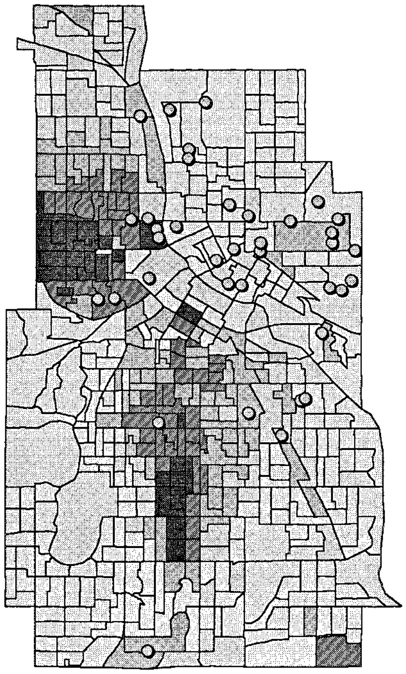

Figure 2. City of Minneapolis, percent African American and TRI sites. Numbers in parentheses represent counts of block-groups in each category.

Using this simple measure of proximity—residence within or outside TRI block groups—significantly different results are found among the variables. Our comparison is based on computing a ratio of the poverty rates between block groups with and without a TRI site, labeled the 'proximity ratio'. The change for the white population, for instance, is 22%/11% or 2.0—whites residing in a block-group containing a TRI site are twice as likely to live below the poverty line than those in a block group not containing a TRI site. Although the poverty rates are consistently higher in TRI block groups (see Table 1), the

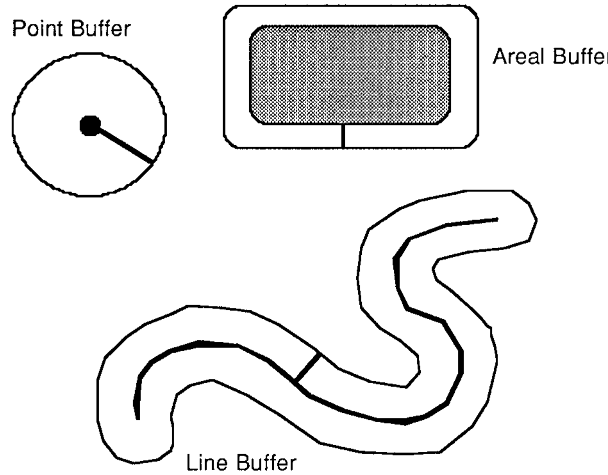

Figure 3. Examples of point, line and areal buffers.

proximity ratio is highest for the white population (2.00), with minorities having ratios of 1.80 (Hispanic), 1.23 (American Indian), 1.15 (Asian), and 1.07 (African American). Note also that the proximity ratio for children under 5 is 1.47. Overall, the proximity ratio is 1.67 for the entire population, which is expected given the relatively high percentage of white persons in the city. In other words, Whites and Hispanics living close to TRI sites are almost twice as likely to be poor as those living further away, and for young children in 1990 poverty is almost 50% greater. African Americans, American Indians and Asians close to TRI sites are likely to be in poverty, but the poverty rate for these groups is not much greater close to a TRI site than further away. For these groups, the likelihood of being in poverty when living close to a TRI site increases by between 7% and 22%. Thus, there is a complex interaction between race, poverty, and proximity to TRI sites. Proximity ratios tend to be higher for groups with lower overall poverty rates. McMaster et al. (1997) addressed the reasons for these patterns based on the industrial history of Minneapolis.

Method 2: Buffer Analysis

A common type of analysis with GISs is that of buffer analysis, which is a spatial analytic technique for assessing proximity within a certain distance of a point, line, or area

Table 1. Poverty rates, proximate and non-proximate block groups, for different races and young children

Proximity measure	Whites	African Americans	American Indians	Asians	Hispanics	Population aged 0–5	Total
Within TRIBG	22	43	64	52	47	47	30
Outside TRIBG	11	40	52	45	26	32	18
Proximity ratio[a]	1.98	1.07	1.23	1.15	1.80	1.47	1.67

[a]The proximity ratio is the ratio of the within-TRIBG poverty rate and the outside-TRIBG poverty rate.

feature. As illustrated in Figure 3, point buffers identify populations within a given radius of a TRI site, areal buffers can be computed around large Superfund sites, and line buffers can track exposure along a railroad line carrying hazardous materials. Although a relatively crude (purely distance based) measure, the application of simple buffers is the primary method that most GISs use to assess proximity.

In the case of environmental equity analyses around a TRI site, the buffer is drawn at a pre-defined distance, the block groups are identified that are within or intersect with the area in the buffer, and information about the populations in these block groups is used to estimate the characteristics of the population inside the buffer. This estimate is arrived at by summing the populations of all block groups, weighted by the fraction of the area of that block group that is inside the buffer.

Figure 4 illustrates 1000-yard buffers calculated for the TRI sites in Minneapolis, depicted with overall poverty rates. In this analysis, we examine the poverty characteristics of the six population subgroups for buffers constructed at three distances—100 yards, 500 yards, and 1000 yards. Admittedly, without a deeper knowledge of certain geographical processes (for instance, wind dispersion), the selection of any buffer distance is somewhat arbitrary. The use of three distances is experimental, with the primary purpose of determining whether the results of the analysis vary significantly with the choice of buffer. The results of the buffer analysis are recorded in Table 2, in the same format as in Table 1.

One can see the variations both among the subpopulation groups and buffer distances. At the 100-yard buffer distance the proximity ratio is highest for Whites (1.83), followed by Hispanics (1.66), African Americans (1.27), Asians (1.26), and American Indians (1.13). The proximity ratio for children living within 100 yards of a TRI site is 1.48. Note also that these differences are very similar to those presented for the spatial coincidence method.

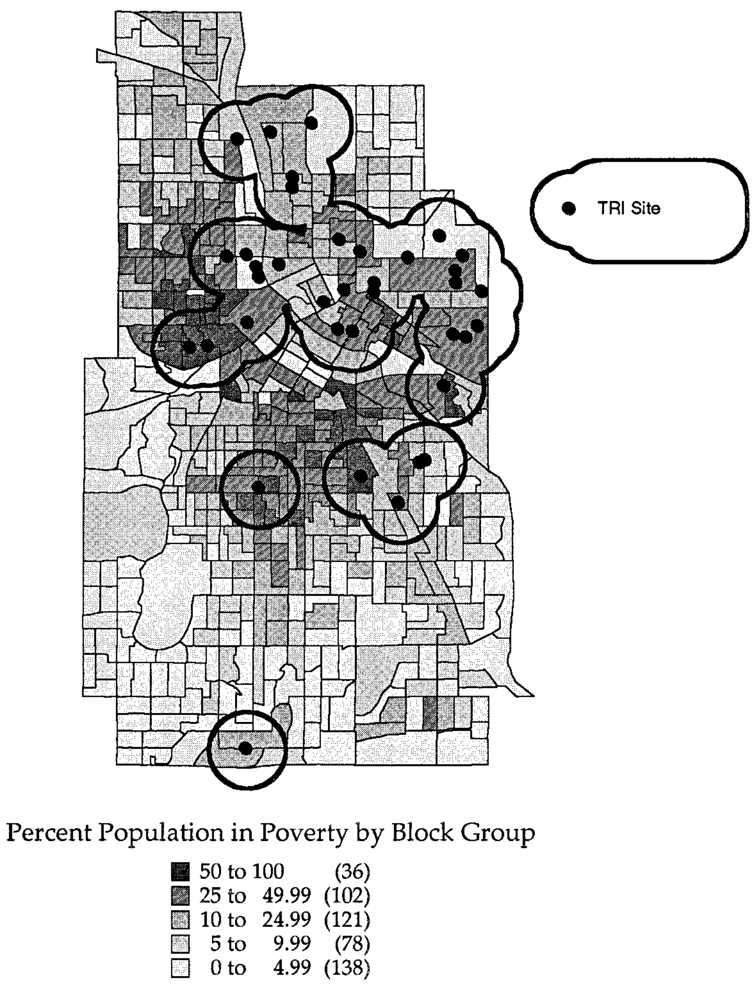

Figure 4. City of Minneapolis, percent population in poverty and 1000-yard TRI buffers.

Table 2. Poverty rates inside and outside buffers, for different sub-populations

Proximity measure	Whites	African Americans	American Indians	Asians	Hispanics	Population aged 0–5	Total
Within 100-yard buffer	22	52	61	58	48	49	32
Outside 100-yard buffer	12	41	54	46	29	33	18
Proximity ratio	1.83	1.27	1.13	1.26	1.66	1.48	1.78
Within 500-yard buffer	22	51	64	57	40	51	33
Outside 500-yard buffer	11	40	52	43	27	31	17
Proximity ratio	2.00	1.28	1.23	1.33	1.48	1.65	1.94
Within 1000-yard buffer	20	50	63	58	39	53	31
Outside 1000-yard buffer	9	36	46	34	23	24	14
Proximity ratio	2.22	1.39	1.37	1.71	1.70	2.21	2.21

'In' records the percentage of populations below poverty inside a given buffer, while 'out' records the percentage of populations below poverty outside the buffer.

Extending the buffer distance from 100 to 500 yards makes remarkably little difference to the proximity ratios. This lack of variation is, however, in large part an artifact of the spatial resolution of the enumeration units from which poverty rates are calculated. The block groups themselves are generally not larger than the area inside a 500-yard buffer (see Figure 1). Thus in each calculation, because of the size of the enumeration units, the population estimates inside the buffers are based on essentially the same geodemographic information.

Analysis of the 1000-yard buffer shows some significant changes from the other buffer analyses, however (see Table 3 summarizing the proximity ratios). In all cases the proximity ratio is higher, and for several racial/ethnic groups, this ratio significantly jumps. In particular, note the increase in the proximity ratio for American Indians (1.23 at 500 yards to 1.37 at 1000 yards), Asians (1.33 to 1.71), and Hispanics (1.48 to 1.70). Between the 500 yard and 1000 yard calculations, the ratio jumps from 1.65 to 2.21 for children under 5. Of course the change for the white population (2.00 to 2.22) significantly affects the overall change (from 1.94 to 2.21). At this distance of 1000 yards, the buffer has moved beyond the extent of one block-group in any direction from a TRI site, and is capturing a greater number of census block groups. It is significant that use of a larger buffer results in increased differences between poverty rates inside and outside the buffer because, in the limit, i.e., when the buffers are so large that they encompass all of Minneapolis, the poverty levels inside the buffer will fall to the Minneapolis average.

How then can one compare and generalize from these results? First, based on the findings from the two proximity measures—spatial coincidence and buffering—one finds that the selection of the buffer size is critical: the size of the buffers must be carefully considered in relation to the resolution of the enumeration units. The results for spatial coincidence and the 100 and 500 yard buffers are very similar, as explained above. Thus, there is little benefit of applying small buffers over simply calculating the spatial coincidence values. However, as one increases the buffer size, it is apparent that more concentrated poverty is captured meaning that, at least at 1000 yards, poverty rates are still increasing. Further sensitivity analysis is needed to determine where, exactly, these rates begin to decline—something which will undoubtedly be dependent on the particular place analyzed.

Second, some common patterns of environmental equity/inequity emerge for all definitions of proximity, the three buffer distances as well as the block group definition previously presented (Figure 5), suggesting some empirical patterns of potential exposure to TRI emissions which can be taken to be reasonably robust; they are not dependent on exactly how proximity is defined. Proximity ratios always exceed one; for all populations, people living near TRI sites are more likely to be poor. In most cases (with the exception of Hispanics), the proximity ratio increases as the buffer is extended to 1000 yards; for broader

Table 3. Differences in proximity ratios by geodemographic variables and proximity measures

Proximity measure	Whites	African Americans	American Indians	Asians	Hispanics	Population aged 0–5	Total
Block groups	1.98	1.07	1.22	1.15	1.80	1.46	1.72
100-yard buffer	1.83	1.27	1.13	1.26	1.66	1.48	1.78
500-yard buffer	2.00	1.28	1.23	1.33	1.48	1.65	1.94
1000-yard buffer	2.22	1.39	1.37	1.71	1.70	2.21	2.21

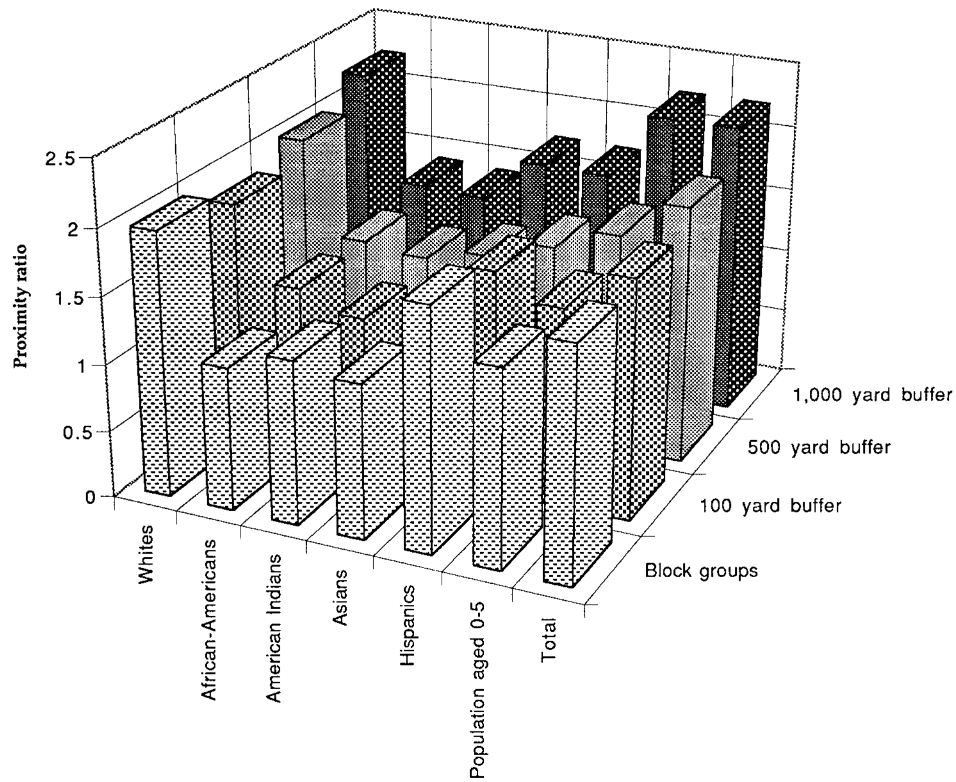

Figure 5. Differences in proximity ratios by geodemographic variables and proximity measures.

definitions of proximity, poverty is a larger discriminating factor for those at greater risk of potential exposure. For those racial groups with the highest poverty rates in Minneapolis (African Americans, American Indians and Asians), the proximity ratios are lowest (with the exception of Hispanics in the 1000 yard buffer case). It remains to be determined, however, whether these patterns are of any significance; whether, for example, the lower proximity ratios for African Americans, American Indians and Asians are so low that they can be regarded as essentially equal to one. It is to these issues that we now turn.

Randomization tests for environmental equity

The conclusion that the proximity ratio exceeds one in all cases, and the considerable disparities across the subpopulations in the size of the proximity ratio, give rise to important questions about what significance can be attached to proximity ratios. In this section we describe and utilize a randomization strategy, designed to quantify the likelihood that the observed proximity ratios are significant. For thirty years, randomization methods have been used for statistical inference with spatial data (Cliff and Ord, 1973; Besag and Diggle, 1977). It is typical of geographic data that nearby observations are spatially autocorrelated (i.e., nearby observations tend to have correlated values) which, like serial autocorrelation, results in inconsistent or biased sample statistics and biased statistical inference. Autocorrelated data have lower degrees of freedom, meaning that use of standard rules of statistical inference in the presence of positive spatial autocorrelation results in greatly increased chances of erroneously rejecting the null hypothesis, even for simple correlation analysis (Haining, 1990). Significant effort has been devoted to developing corrective methods in order to adjust standard procedures to take into account observed levels of spatial correlation, but these are often of limited utility in real situations (where, for example, the moments of spatial autocorrelation statistics vary over space).

Randomization is essentially a methodology for simulating the distribution of a sample statistic based on the characteristics of the particular case being analyzed, and evaluates the 'significance' of the observed statistic by comparing it to this distribution. In other words, it can be regarded as a form of distribution-free statistical test which now has become the standard for testing the significance of spatial distributions (Hubert et al., 1981; Griffith, 1988; Getis and Ord, 1992). In this case, the hypothesis to be investigated is whether the ratios of poverty percentages between proximate and non-proximate subpopulations, as recorded in Tables 1 and 2, are large by comparison to what would be observed if the TRI sites had been located randomly within Minneapolis. Put otherwise, the question is whether observed proximity ratios are unusually high by comparison to those that might have resulted by chance. Since this test is not a significance test in the usual sense, we will place 'significant' in quotations in the subsequent discussion.

For any randomly chosen configuration of TRI sites, poverty rates for proximate populations can be calculated using either the block group or the buffer definition of proximity. The differences between the poverty rates for proximate populations and the city-wide average poverty rate for that subpopulation will vary significantly depending on the particular random configuration examined. If these differences are averaged for a number of such configurations, however, then they will converge towards zero as the number of configurations increases. This is because the expected poverty rate of randomly chosen proximate populations, like that of non-proximate populations, equals the poverty rate for that population in Minneapolis as a whole. The degree to which observed differences in poverty rates for a particular population sub-group are unusually high will depend on where this observed difference falls within the distribution of possible poverty rates generated by the randomization process. Observed poverty rates located in the extreme upper tail of the simulated distribution will be 'significant', whereas those close to the mean of the simulated distribution will not be 'significant'.

This procedure is operationalized as follows. A random location for a TRI site is generated by randomly selecting Cartesian coordinates for that location from a uniform random distribution of numbers, subject to the constraint that the location lies within the municipal boundary of Minneapolis. Since there are 38 TRI sites in Minneapolis in 1995, choice of 38 such sites constitutes a single random configuration. For each such configuration, the proximate population is identified as those within the same block group as a randomly chosen site, or within buffers centered on these simulated sites. We calculated (or, in the buffering case, estimated) the number of people of each subpopulation below the Federal poverty level, the total number of that subpopulation, and the poverty rate, for proximate subpopulations.

This procedure was then repeated 1500 times to generate a simulated distribution of poverty rates for each subpopulation, giving 1500 simulated estimates of the percentage of the proximate subpopulation below poverty. The number of simulated random configurations (1500) was determined endogenously, by keeping track of the weighted mean poverty rate for proximate populations, taken over all simulations, for each subpopulation, and determining how many simulations were necessary before that average converged closely to its expected value (the city-wide average for that population group). It should be noted that the simulations reported here do not take into account all of the information in the case study. For example, in practice TRI sites cannot locate anywhere in Minneapolis, but only in areas zoned for industrial and commercial activities, and indeed in general the locations of commercial and industrial facilities are geographically clustered rather than random. We are carrying out further simulations that constrain the randomization process to take into account the location of commercial and industrial land, but the results reported here provide at least a first estimate of the degree to which the observed proximate populations experience unusually high poverty rates.

In Table 4, we record where the observed poverty rates (Tables 1 and 2) fall within these simulated distributions, as percentiles. Figure 6 illustrates the distribution of simulated values, and the location of the observed poverty rate relative to this distribution, for the case of whites and a 100-yard buffer. In this case, the observed poverty rate exceeds all of the 1500 simulated values, which we record in the table as the 99.9th percentile. By any measure, the observed poverty rate is unusually high for the proximate population in such a case. We will follow normal statistical conventions in this analysis, using a value of 95% or greater as indicating a poverty rate for the proximate population that is 'significant', i.e., high enough to reject the null hypothesis of no relationship between proximity to a TRI site and the percentage of population in poverty.

Table 4 suggests that as the geographical definition of proximity is enlarged, from 100-yard to 1000-yard buffers, the observed values become increasingly large relative to the distribution of simulated values. Indeed, in the case of the 1000-yard buffer, for all subpopulations the observed poverty rate is larger than any of the 1500 simulated values. It can be inferred from this that the observed

Table 4. Minneapolis: Observed poverty levels as percentiles of the simulated distribution for populations near TRI sites, 1995

Proximity measure	Whites (%)	African Americans (%)	American Indians (%)	Asians (%)	Hispanics (%)	Population aged 0–5 (%)	Total (%)
Block groups	99.9[a]	86.8	87.1	73.1	80.1	97.9	99.9
100-yard buffer	99.9	95.5	78.8	86.4	94.1	97.8	99.9
500-yard buffer	99.9	98.8	96.6	88.8	94.5	99.9	99.9
1000-yard buffer	99.9	99.9	99.9	99.9	99.9	99.9	99.9

[a]Observed value greater than 1500 simulated values.

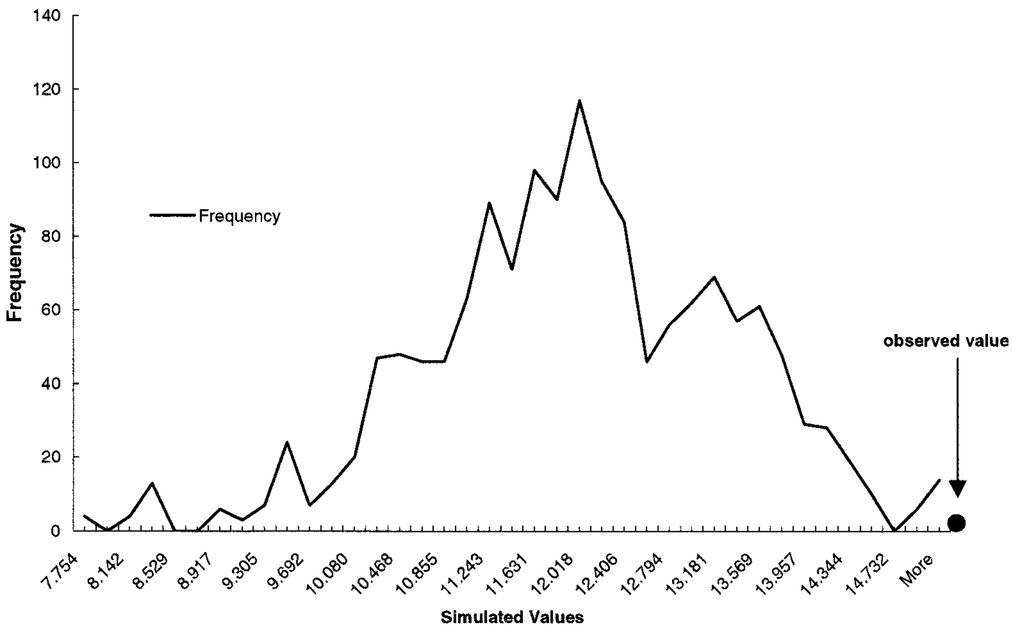

Figure 6. Histogram of percentage whites in poverty within 100 yards of randomly simulated TRI sites.

poverty rates within the 1000-yard buffers are too high to have occurred by chance. As a result of a combination of the processes driving the location of industrial sites and those driving housing market and residential dynamics, poor people and industries releasing toxic chemicals have clustered in the central area of Minneapolis. For the 1000-yard buffer, people potentially exposed to toxic chemical releases are more likely to be poor.

There are notable differences between the subpopulations for more localized definitions of proximity, however. Observed poverty rates for proximate Asian and Hispanic populations are not high enough to reject the null hypothesis in the other cases, and the same is true for American Indians (for the block group and 100-yard buffers) and African Americans (for the block group only). The null hypothesis is consistently rejected, however, for whites, for all children under five, and for the total population.

Comparing Tables 3 and 4, there is no clear relationship between the proximity ratios (Table 3) and the 'significance' of observed poverty rates for proximate populations (Table 4). Comparable proximity ratios for different subpopulations (e.g., Hispanics in the block-group case and whites for the 100-yard buffer) suggest opposite inferences about their significance. Even for the same subpopulation (e.g., Hispanics), the ratio can decrease as the buffer is expanded, whereas the significance of that ratio increases. This suggests that standard significance tests can give unreliable results, and that the kinds of simulations of sampling distributions described here are necessary to make systematic inferences about the importance of observed differences in poverty rates between proximate and non-proximate populations.

Conclusions

Both theoretical and applied research in the area of environmental risk assessment in general, and equity studies specifically, is taking increasing advantage of GIS technology, rich geographical databases, and advanced methods of data visualization. Environmental equity analysis is intrinsically geographical, and the application of geographic information systems provides great opportunity for geographers to play a vital role in this socially relevant arena of research. To date, research on environmental equity has been plagued by contrasting results, which to a significant degree are due to the failure to pay close attention to the effects of measures of proximity, scale, resolution and boundary effects, and choice of geodemographic variables.

The research presented here applies some standard and novel geographic approaches to assess the degree of inequity to TRI site exposure in the City of Minneapolis, MN. Two measures of proximity to TRI sites—'spatial coincidence' and buffering—were applied to poverty rates for Whites, African Americans, American Indians, Asians, Hispanics, children below the age of 5 and the total population. The results of these analyses indicate that there is a stronger association between white poverty and total population in poverty and TRI location, than between minorities in poverty and TRI location. Overall, a higher percentage of poor people live near TRI sites. The relationship was similar for spatial coincidence and small buffers, but was stronger for the larger buffer of 1000 yards. Given our concern about the significance of observed patterns of environmental equity/inequity, we carried out a series of randomization experiments to 'simulate' a hypothetical set of TRI distributions, using the same spatial coincidence and buffering measures of proximity. Randomization is a methodology for simulating the distribution of a sample statistic based on the characteristics of the case being analyzed, and evaluates this 'significance' of the observed statistic by comparing it to this distribution. Even though there are considerable differences in the observed proximity ratios for the various subpopulations, the simulation results indicate that, broadly speaking, observed TRI locations in Minneapolis were associated with unusually high poverty rates. No systematic relationship between the observed proximity ratios and the significance of the higher poverty rates near TRI sites could be demonstrated. Thus we recommend that environmental equity research utilize such randomization approaches to examine observed patterns for significance. Nearly all places have unique characteristics that will often be associated with distinctive patterns of environmental equity/inequity. A simulation approach allows for the generation of a robust distribution-free assessment, sensitive to geographical particularities.

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