Disproportionate Proximity to Environmental Health Hazards: Methods, Models, and Measurement

We sought to provide a historical overview of methods, models, and data used in the environmental justice (EJ) research literature to measure proximity to environmental hazards and potential exposure to their adverse health effects. We explored how the assessment of disproportionate proximity and exposure has evolved from comparing the prevalence of minority or low-income residents in geographic entities hosting pollution sources and discrete buffer zones to more refined techniques that use continuous distances, pollutant fate-and-transport models, and estimates of health risk from toxic exposure.

We also reviewed analytical techniques used to determine the characteristics of people residing in areas potentially exposed to environmental hazards and emerging geostatistical techniques that are more appropriate for EJ analysis than conventional statistical methods.

We concluded by providing several recommendations regarding future research and data needs for EJ assessment that would lead to more reliable results and policy solutions. (*Am J Public Health.* 2011;101:S27–S36. doi:10.2105/AJPH.2010.300109)

Jayajit Chakraborty, PhD, Juliana A. Maantay, PhD, and Jean D. Brender, PhD, RN

ENVIRONMENTAL JUSTICE **(EJ)** is defined broadly as the disproportionate distribution of environmental "goods" and "bads," with the burden of the bads and the dearth of the goods falling mainly on racial and ethnic minorities, lower income populations, and other vulnerable groups. Since the 1980s, a large body of literature on EJ has emerged, mainly focused on areas in the United States and often using geographic information systems (GIS) to assess the proximity of vulnerable subpopulations to environmental hazards as a proxy for exposure and the potential for deleterious health impacts.[1–11] GIS technology is well suited to EJ research because it allows for the integration of multiple data sources, cartographic representation of data, and the application of various spatial analytical techniques for proximity analysis.[11,12] Although maps are effective in visually demonstrating the disproportionate spatial distribution of environmental hazards, researchers have commented on the challenges and limitations inherent in spatial analysis and questioned GIS's efficacy in demonstrating pollution's health impacts. Spatial and attribute data deficiencies and methodological problems, especially those related to geographical considerations, have been well documented.[6,11,13–23] However, development of methods for producing more meaningful spatial analyses is feasible, and health geographers and other researchers have been using GIS to demonstrate the correspondence among factors such as proximity to hazards, disproportionate exposure, and health disparities.

We reviewed methods commonly used by EJ researchers in articles that were selected to provide a comprehensive overview and synopsis of quantitative research on EJ and disproportionate proximity to environmental hazards over the past 2 decades. We searched these databases for relevant published literature: Sociological Abstracts, Social Science Citation Index, Science Citation Index, and the National Library of Medicine's PubMed. We initially selected studies by using the search terms *environmental justice, environmental equity,* and *environmental racism.* We attempted to find studies exhibiting as wide a range as possible in terms of geographic extent studied, variety of hazards examined, and analytical techniques used. We excluded literature review articles and those using purely theoretical or qualitative approaches. The final list of references selected for our critical review of EJ research methodology consisted of quantitative case studies (n = 80) that examined racial–ethnic and socioeconomic disparities in the distribution of, or proximity to, environmental health risks, pollution sources, and undesirable land uses. Most of these studies indicated a disproportionate distribution of environmental burdens with respect to both race and socioeconomic status (SES). Although SES variables pointed to more significant risks of exposure than race,[17,24–27] race tended to be significant even when controlling for SES.[28–31] We summarized the most frequently cited and significant studies (n = 55) reviewed in Online Supplemental Table 1 (available at www.ajph.org), which includes the study parameters and scope, pollution indicators used, methodology used, and findings.

We provide a historical overview and critical assessment of (1) analytical approaches used to spatially define the boundaries of areas potentially exposed to environmental hazards, (2) methods for estimating population characteristics of such areas, and (3) emerging geostatistical techniques that address limitations of conventional approaches.

SPATIAL DEFINITION OF PROXIMITY AND EXPOSURE TO HAZARDS

Spatial coincidence, in the context of EJ research, is a technique that assumes potential exposure to environmental hazards is confined to the boundaries of predefined geographic entities or census units containing such hazards.

Spatial Coincidence Analysis

Although its implementation has changed over time, the most widely used and traditional method of spatial coincidence analysis, known as unit–hazard coincidence,[32] uses the presence of a hazard source within an analytical unit as a proxy for environmental exposure. Sociodemographic characteristics of spatial units containing a hazard (host units) are compared with those that do not contain such hazards (nonhost units) to determine disproportionate proximity or exposure. Several influential national-level EJ studies have used the location of hazardous facilities within zip codes[33,34] or census tracts[35,36] to represent risk burdens. Some studies have even used the county as a spatial unit for coincidence analysis.[37,38]

The choice of analytical unit to represent the host area for EJ research has been the subject of considerable debate because different units potentially lead to different conclusions regarding the role of race–ethnicity or income.[8,17,39–41] Regardless of the analytical unit selected, the unit–hazard coincidence method is problematic for 3 reasons. First, most applications do not draw a distinction between spatial units that host 1 hazard source and those that contain several sources. Second, this approach ignores boundary effects that deal with the possibility that a facility could be so close to the edge of a host unit that a neighboring nonhost unit could be equally exposed to pollution. Third, this method assumes that exposure to hazards is distributed uniformly within host units and restricted only to their boundary. Predefined geographic entities or census units, however, are unlikely to represent the actual size or shape of the area exposed to adverse health effects.

Figure 1a illustrates a typical application of the unit–hazard coincidence method, based on the distribution of 12 hazardous facilities across census tracts. Most facilities are located near the boundaries of multiple tracts and closer to adjacent nonhost tracts than to the far end of their own host tract. Their adverse impacts are unlikely to be confined only to their host tracts. Additionally, all tracts with facilities are categorized as host tracts, although the number of facilities within each host tract varies.

The inability to distinguish between host units on the basis of the magnitude of hazards can be addressed by summing the number of facilities or the volume of pollutants released within each unit. Instead of treating all host units equally, several EJ studies have extended the basic coincidence approach by enumerating the frequency of hazardous facilities within block groups,[40] tracts,[3,42,43] zip codes,[44] and counties.[45,46] Databases such as the Toxic Release Inventory (TRI), which provides detailed data on annual quantities of toxic chemicals released at each TRI facility, allow a more refined assessment of emission volume within each host unit. Although some EJ studies have relied on the total pounds of TRI pollutants,[2,37,44,45,47,48] others have used toxicity indicators such

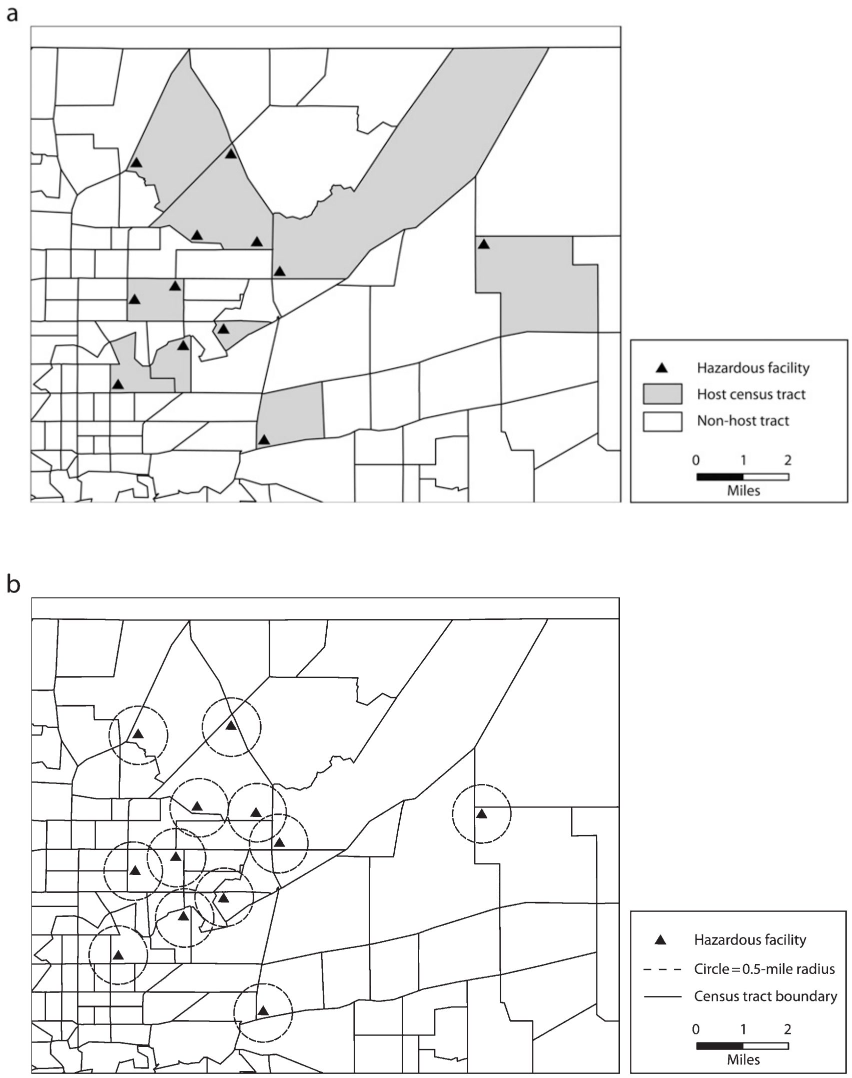

FIGURE 1—Spatial definition of proximity to environmental hazards using (a) spatial coincidence to select host census units, (b) circular buffers of uniform radius around facilities of concern, and (c) plume footprint for a hypothetical chlorine release scenario using the Areal Locations of Hazardous Atmospheres model.

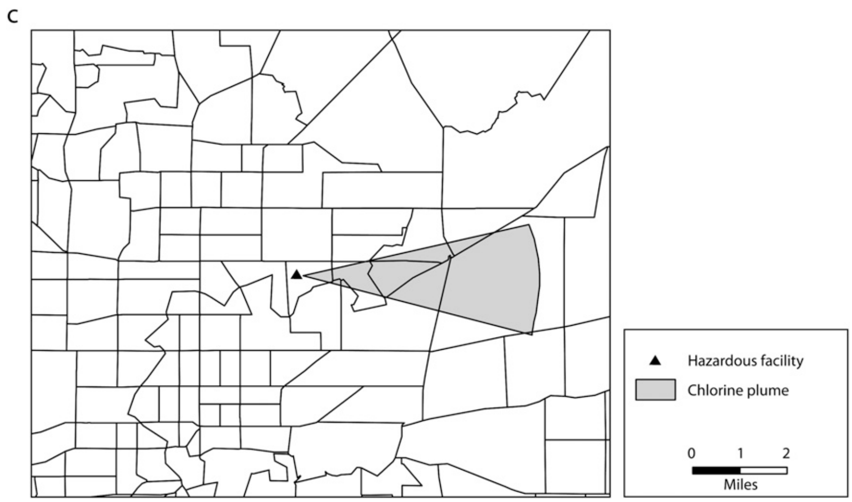

FIGURE 1—(Continued).

as threshold limit values to weight annual emissions of each chemical in each spatial unit.[2,17,47,49,50] Applications of spatial coincidence analysis that use emissions and toxicity data, however, are still limited by the inability to consider the exact geographic location of the hazard within the host unit and accurately determine the spatial extent of toxic exposure.

Distance-Based Analysis

To address the limitations of the spatial coincidence approach, EJ studies have analyzed proximity by measuring the distance from environmental hazard sources. Although several distance-based techniques have been suggested, the most widely used method is buffer analysis. Buffer generation is an analytical technique provided by GIS software for creating new polygons around point, line, or area features on a map (Figure 1b). Since the mid-1990s, GIS-based circular buffers of various sizes have been used in EJ studies to identify areas and populations at risk.[4,7,9,11,32,47,51–65] Sociodemographic characteristics of areas lying inside buffer zones are typically compared with the rest of the study area to determine disproportionate proximity or exposure to the hazards of concern. The radii of circular buffers in EJ research have ranged from 100 yards[11] to 3 miles,[10,32] but distances of 0.5 and 1.0 mile are used most frequently.[4,7,9,32,47,52–59,62,65] Instead of using a single radius or buffer, several studies have constructed multiple circular rings at increasing distances from hazard sources.[9,11,51,60,61,64]

Circular buffers provide a more accurate geographic representation of potential exposure to hazards than spatial coincidence because the adverse effects are not assumed to be restricted to the boundaries of the host spatial unit. However, specific limitations are associated with their application in EJ research. The radius of the circle is often chosen arbitrarily, and buffers around all hazards in a study area usually have the same radius (Figure 1b). The properties and quantities of substances stored or released at each individual facility or the environmental fate and transport of emitted pollutants are rarely incorporated in the determination of buffer radii to represent the spatial extent of exposure. Another problem is the assumption that the adverse effects of a hazard are limited only to the specified circular area and the areas outside remain unaffected. Although this binary assumption makes comparisons convenient, the results are highly sensitive to the choice of buffer radius, as demonstrated in studies using multiple circles around facilities of concern. A discrete measurement is also unlikely to reflect a more continuous or gradual reduction in exposure with increasing distance from the hazard.[12,66]

Continuous distances, based on the calculation of the exact distance between each hazard and the location of the potentially exposed population, are an alternative to the discrete distances commonly used for buffer analysis. Several EJ studies used the distance from the centroid of each census tract or block group to the nearest hazard source as an indicator of proximity.[8,67–72] The analysis of continuous distances can be enhanced by using a cumulative distribution function. A cumulative distribution function is essentially a graph that depicts the cumulate percentage of observations falling below every threshold value. Applied to any set of hazardous facilities, a cumulative distribution function plot can illustrate how the relative size of the exposed population increases with distance. Several EJ studies demonstrated that cumulative distribution functions are well suited to assessing disproportionate proximity because they overcome the limitations of choosing arbitrary and discrete buffer distances.[12,66–68]

Although most proximity-based analyses of EJ assume that the adverse effects of a hazard decline with distance in a linear fashion, a few studies have used curvilinear functions to model proximity. One study hypothesized 3 functional forms of exposure to analyze proximity to TRI facilities in Florida and used the natural logarithm of the distance to the nearest facility as a proxy for exposure.[71] A GIS-based distance decay modeling technique was also developed and applied to evaluate TRI proximity in Detroit.[73] Although this technique was flexible enough to incorporate any distance decay function, several curvilinear and reverse curvilinear functions were used to estimate neighborhood proximity to TRI facilities.

Although distance-based approaches to EJ analysis have evolved from the use of discrete buffers to continuous functions, they are still limited by the fact that the actual extent of toxic exposure may not be a simple function of distance. Additionally, distance-based analyses ignore directional biases in the distribution of environmental hazards by assuming that their adverse effects are equal and uniform in all directions. Although physical processes rarely operate in a perfectly symmetrical (isotropic) manner, distance-based methods assume that exposure is invariant to prevailing wind direction and other factors that influence the movement and dispersal of emitted pollutants.

Pollution Plume Modeling

To delineate the boundaries of airborne toxic exposure more accurately, EJ studies have used data on chemical emissions and local meteorological conditions to model the environmental fate and dispersal of pollutants released from hazard sources. Geographic plume analysis is a methodology that integrates air dispersion modeling with GIS to estimate areas and populations exposed to airborne releases of toxic substances.[4,74] Dispersion models typically combine data on the quantity and properties of a released chemical with data on site characteristics, release parameters, and atmospheric conditions to delineate the boundaries of the area potentially exposed to the chemical's spreading plume (plume footprint). The footprint represents the area in which ground-level concentrations of the pollutant are predicted to exceed a user-specified threshold level (Figure 1c). Most applications of geographic plume analysis for EJ research have relied on Areal Locations of Hazardous Atmospheres (ALOHA), an air dispersion model designed for short-duration chemical releases. This model has been used to generate a single plume footprint,[74] composite footprints reflecting historical weather patterns,[4,75] or circular buffers based on worst-case accident scenarios.[70,75–77] Other EJ studies have used the Industrial Source Complex Short Term air dispersion model,[78–80] ash deposition models,[81] and noise pollution models.[5,82] Exposure to ground and water contamination, however, has received limited attention in EJ research.

The application of geographic plume analysis allows the concentration of toxic pollutants released from a hazard source and their health risks to decline continuously with increasing distance from the emitting source and to vary according to compass direction. Plume-based buffers thus address the problems of previous approaches that assume that residing either in a census unit containing a hazard (spatial coincidence) or within a specific distance from a hazard (distance based) results in toxic exposure. However, plume modeling has certain limitations. First, dispersion models typically require large volumes of data on chemical properties, operational parameters of each release, and local meteorological conditions. Second, some dispersion models such as ALOHA assume that topography is flat and are unable to provide accurate concentration estimates when the atmosphere is stable or wind speeds are low. Third, the creation of plume modeling data to encompass all facilities and chemical emissions in a large study area is a time-consuming and expensive process.[73] Consequently, few national or regional plume model data sets have been constructed, and existing data sets are limited to specific types of hazards.

Data sets derived from pollutant fate-and-transport modeling that cover the entire United States include the Risk-Screening Environmental Indicators (RSEI) and National-Scale Air Toxic Assessment (NATA). These national databases developed by the US Environmental Protection Agency are particularly appropriate for EJ research because they allow researchers to estimate potential health risks associated with specific pollutants and spatial units. Additionally, the plume modeling and risk assessment techniques used to derive these data consider various factors such as wind speed, wind direction, air turbulence, smokestack height, and rate of chemical decay and deposition. The RSEI model is used to estimate chronic health risks on the basis of toxicity and atmospheric dispersion of chemicals emitted by TRI facilities. EJ studies have used RSEI risk scores to analyze exposure to TRI pollutants in the entire United States[83,84] and in Philadelphia, Pennsylvania,[85] and Tampa Bay, Florida.[86] Because the pollution plumes used to obtain the risk estimates can extend in any direction for up to 44 miles from a TRI facility, the RSEI modeling technique has the advantage of allowing emissions in a spatial unit to affect people living in other units. The NATA has also emerged as an important tool for estimating exposure concentrations and public health risks associated with inhalation of hazardous air pollutants from multiple emission sources. Census tract–level estimates of cancer risk from the 1996 NATA have been used for EJ analysis in Maryland,[24] California,[31] and 309 US metropolitan areas.[29] The 1999 NATA has been used to evaluate cancer and respiratory risks in Florida[87] and the metropolitan areas of Houston, Texas,[27] and Tampa Bay.[28] The NATA allowed EJ analysis to extend beyond major stationary sources and include smaller emitters, as well as on-road and nonroad mobile sources.

Although plume modeling techniques represent a significant improvement over spatial coincidence and distance-based approaches, they are often based on default assumptions and may not be as accurate as many researchers think. More important, their use is limited to particular research questions (those having to do with specific public health risks) and pollutant types (those covered by the plume models).

POPULATION ESTIMATION TECHNIQUES

Spatial analytical techniques used in EJ research to determine the sociodemographic characteristics of residents proximate to a hazard can be classified into 2 categories, depending on the level of aggregation of the population data. When addresses of all individuals or households relevant to the study are available and can be located on a map, point interpolation is the appropriate method. Street address information is used with a digital street network to determine an accurate location for each individual, using the GIS's geocoding capabilities. The number and characteristics of individuals potentially exposed to a hazard can be estimated by counting points that fall inside a buffer zone (point-in-polygon overlay). The earliest application can be found in a study on waste facilities in Detroit[88] that used survey data to determine whether the racial and economic status of respondents living within circular buffers differed from those of respondents residing outside these buffers. Subsequent EJ studies have used point interpolation to estimate the special needs population in Cedar Rapids, Iowa;[77] characteristics of survey respondents in Fort Lauderdale, Florida; [81] racial and ethnic status of children in Orange County, Florida;[67] and sociodemographic characteristics of respondents to a national survey residing near TRI facilities.[59]

Although point interpolation is easier to implement, a key requirement is availability of street addresses of all individuals relevant to the study. Because individual- or household-level data on residents' sociodemographic characteristics are not publicly available, EJ studies have relied mainly on information collected by the US Census, available at the level of predefined geographic entities. If the area potentially exposed to a hazard is represented by a distance-based or plume-based buffer, the shape and size of the buffer zone is unlikely to match the underlying census units containing population data. A method of areal interpolation (polygon-on-polygon overlay) is necessary to transfer data from census units to the buffer zone boundary (Figure 2).

The simplest method is polygon containment,[4] also referred to as boundary intersection,[32] in which characteristics of a buffer zone are derived through a simple aggregation of census units that are intersected or entirely enclosed by the buffer. A variation of this method includes a cut-off criterion to limit the inclusion of partially enclosed units. The most common practice is to include census units that have more than half of their area within the buffer zone, referred to as the 50% area containment method.[32,58] The centroid containment method,[4,89] in contrast, only selects census units whose geographic centers (centroids) are located within the buffer zone. This method is less likely to provide accurate estimates if the actual residences of people in census units intersected by the buffer are not concentrated near the centroid. The effective buffer zone obtained through either polygon or centroid containment, however, will not resemble the original buffer (circle or plume footprint) because these zones are based on the boundaries of the selected census polygons.

The most widely used interpolation technique is buffer containment,[4] also known as areal apportionment.[32,57] This method includes all census units lying within the buffer and a fraction of the population from units that are intersected by the buffer. This approach has the advantage of retaining the geometry of the original circle or plume used to delineate the buffer. The population of each census unit is typically weighted by the proportion of its area that falls inside the buffer zone.[89] The population and characteristics of each unit are assumed to be distributed uniformly within its boundary. This technique, however, could lead to inaccurate estimates when the residences of people within the unit are concentrated in specific areas instead of being evenly dispersed.

Although no single best technique has emerged, the application of dasymetric mapping in combination with areal interpolation has been suggested as a promising approach.[7,12,90] This technique uses ancillary data (e.g., land use or land cover) to provide a more accurate distribution of the population residing within census units.[8] Studies have suggested that cadastral dasymetric mapping represents a substantial improvement over the use of the aggregated census data.[89,91] In this method, property tax lots (e.g., cadastral data) are used as the unit of data aggregation instead of census tracts or block groups, to achieve a much finer resolution of the population data. Census data are disaggregated to the tax-lot level by means of an expert system that determines which of several population-related variables most accurately capture the actual spatial distribution of people. For example, New York City has approximately 2200 census tracts but nearly 850 000 tax lots; disaggregating the tract population to the tax lot thus provides a considerably more detailed depiction of where people live, which is particularly important in hyperheterogeneous urban environments in which the population distribution can be significantly different even within 1 block. Figure 3 illustrates how land parcel boundaries can be

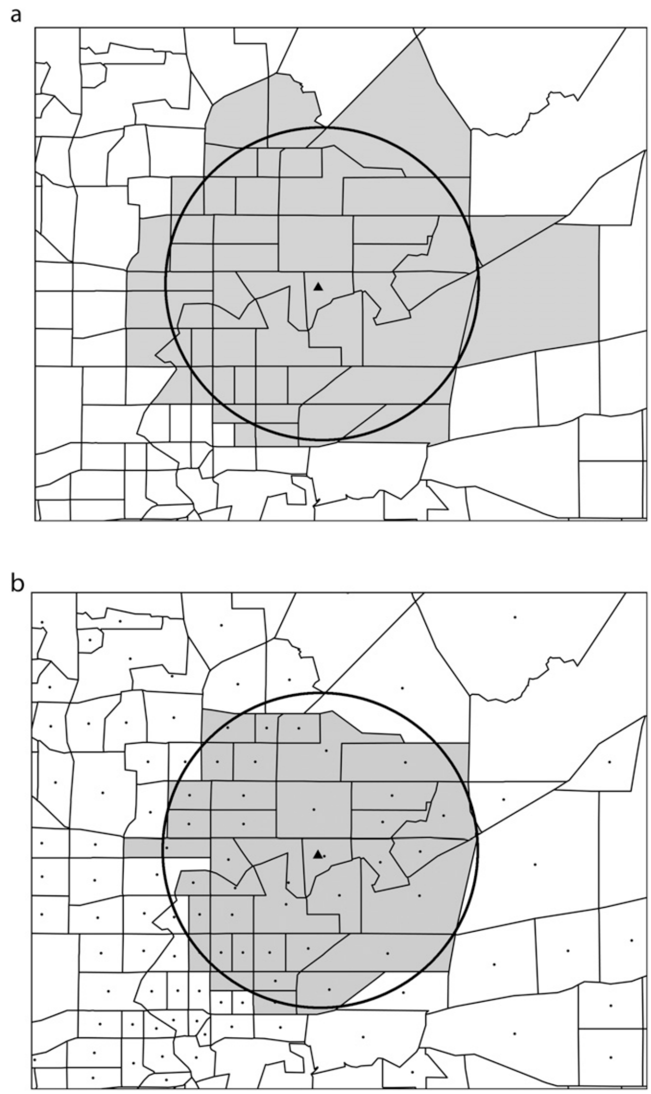

FIGURE 2—Use of areal interpolation to select census units within a circular buffer using (a) polygon containment, (b) centroid containment, and (c) buffer containment.

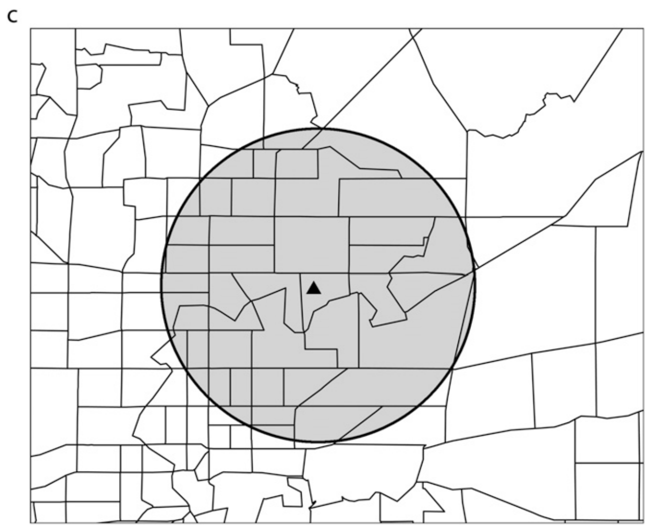

FIGURE 2—(Continued).

used to estimate households within 0.5 mile of a facility. Additional details such as housing tenure, ownership, and values can be used to assess SES for proximate households.

EMERGING GEOSTATISTICAL TECHNIQUES

Most EJ studies have used linear correlation or regression to determine the significance of the association between environmental risk indicators and population characteristics such as race–ethnicity or income. Although least squares regression is an effective and popular technique for measuring relationships between dependent and explanatory variables, it relies on 2 assumptions (independence and homogeneity) that are rarely met by spatially distributed data.

The independence assumption ignores the notion that locational proximity often results in value similarity when most sociodemographic variables are mapped. This concept is often referred to as the first law of geography[92]: Everything is related to everything else, but near things are more related than distant things. This law implies that observations from nearby locations are more similar than what one can expect on a random basis. This phenomenon is known as spatial dependence and more formally as spatial autocorrelation.[93–95] The presence of such autocorrelation can be problematic for classical statistical tests such as regression that assume independently distributed observations and errors. Although EJ analysis is based on spatial data, most studies have assumed observations and residuals to be independent, thus violating one of the key regression assumptions and ignoring spatial effects that could lead to incorrect inferences and biased results. Spatial regression models, such as simultaneous autoregressive models, are statistical models that consider spatial dependence as an additional variable in the regression equation and estimate its effect simultaneously with that of other explanatory variables. The use of spatial regression has increased since the availability of GIS and user-friendly software such as GeoDa,[93] which is capable of implementing underlying spatial econometric techniques. EJ researchers have recently begun to use simultaneous autoregressive models that explicitly consider the effects of spatial autocorrelation.[28,31,96]

The classical regression model also assumes a generating process that is considered to be stationary (homogeneous) and uses a single set of parameters for an entire study area. The use of a single or global regression model assumes that model parameters do not vary spatially and ignores local differences in statistical associations between the dependent and independent variables. Because conventional regression does not account for spatial variability within a study area and provides only global results, it can mask important geographic differences in statistical relationships relevant to EJ.[42] Geographically weighted regression is a local statistical technique for analyzing spatial nonstationarity, defined as when the measurement of relationships among variables differs from

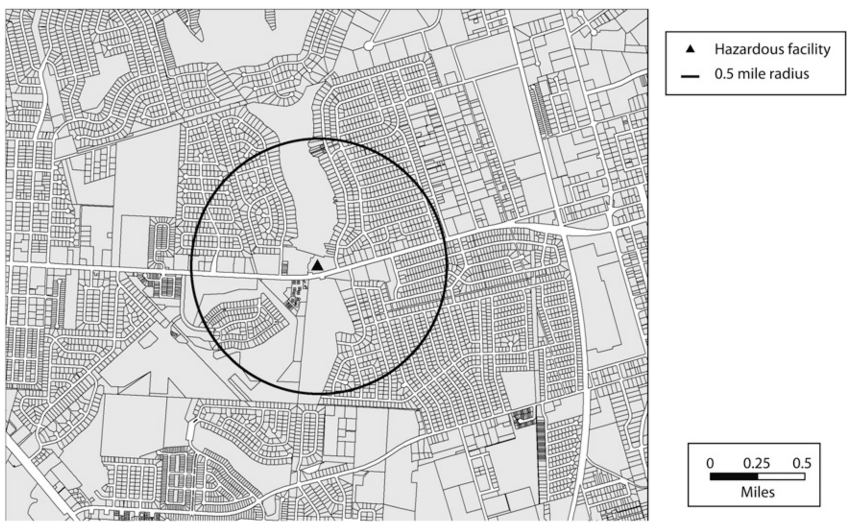

FIGURE 3—Cadastral dasymetric mapping: using land parcels to estimate households within a circular buffer zone.

location to location.[97] Instead of generating a single global regression equation (one set of regression parameters) for the study area, geographically weighted regression produces a separate regression equation (unique set of parameters) for each individual spatial unit. Maps generated from geographically weighted regression have recently been used to examine how statistical associations between environmental risk and sociodemographic factors vary across census tracts in New Jersey[42] and Florida.[87] Figure 4 illustrates how tract-level relationships between cancer risk from air toxics and specific explanatory factors could be significantly positive in some areas, significantly negative in other areas, and nonsignificant at other locations, all within the same state.

CONCLUSIONS

We have demonstrated how the analysis of proximity and exposure to environmental health hazards in EJ research has evolved from simple coincidence analysis and discrete buffer zones to more sophisticated techniques that are based on precise distances between hazards and people, quantity and quality of emitted pollutants, fate-and-transport modeling, and estimates of chronic health risk from toxic exposure. In spite of these improvements, quantitative EJ research remains constrained by several limitations.

First, by using US Census data, most studies have focused exclusively on nighttime exposure. Because census variables represent residences, or people's nighttime locations, they cannot be used to assess daytime risk. An exception is the NATA, which uses census home-to-work commuting and employment data to estimate people's daytime locations. Future EJ research should explore the use of additional data sources to construct temporally sensitive models that examine the daytime distribution of various vulnerable groups. In addition to commuting and employment, information on people in daytime institutions (e.g., schools and daycare centers) can be used to develop an independent model of the population distribution for the hours between 7:00 AM and 5:00 PM to complement census residential data.

A second limitation is the difficulty in obtaining data at a spatial resolution that is sufficiently detailed to reliably demonstrate the connection between environmental exposure and sociodemographic characteristics of people at risk. The lack of address-specific and individual-level information forces most EJ researchers to use aggregated health or census data and make simplistic assumptions about the residential population distribution. Local household surveys and cadastral dasymetric mapping should be used to enhance areal interpolation and more accurately estimate characteristics of at-risk populations.

Finally, it is important to consider that although conventional statistical methods such as correlation or regression are used extensively to analyze EJ and health disparities, these techniques may not be appropriate for analyzing spatial data. Instead of relying only on traditional statistical methods, future research needs to incorporate geostatistical techniques that are more suitable for analyzing spatial data and relationships. Increased education in techniques such as simultaneous autoregressive or geographically weighted regression modeling is necessary to encourage new research incorporating these methods

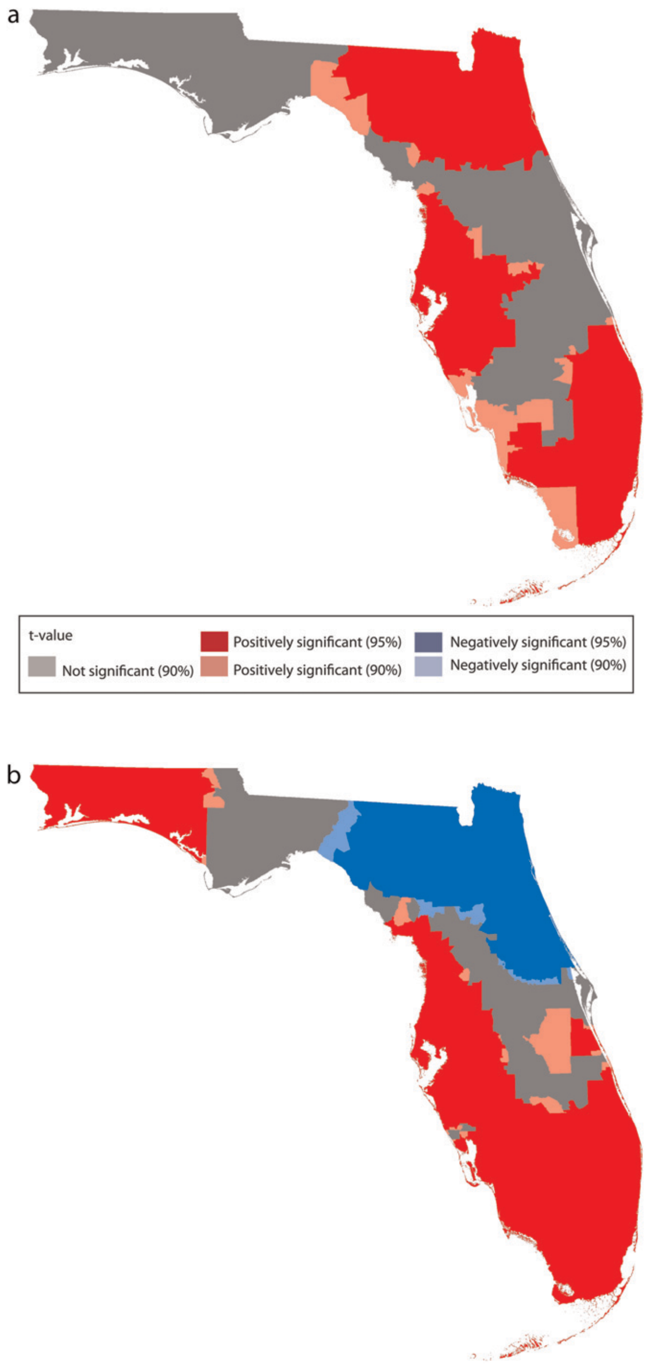

FIGURE 4—Using geographically weighted regression to explore the relationship between cancer risk from non–point (area) sources of air toxics (1999 National-Scale Air Toxic Assessment) and various explanatory variables (2000 Census) in Florida: Distribution of local *t* statistic by census tract.

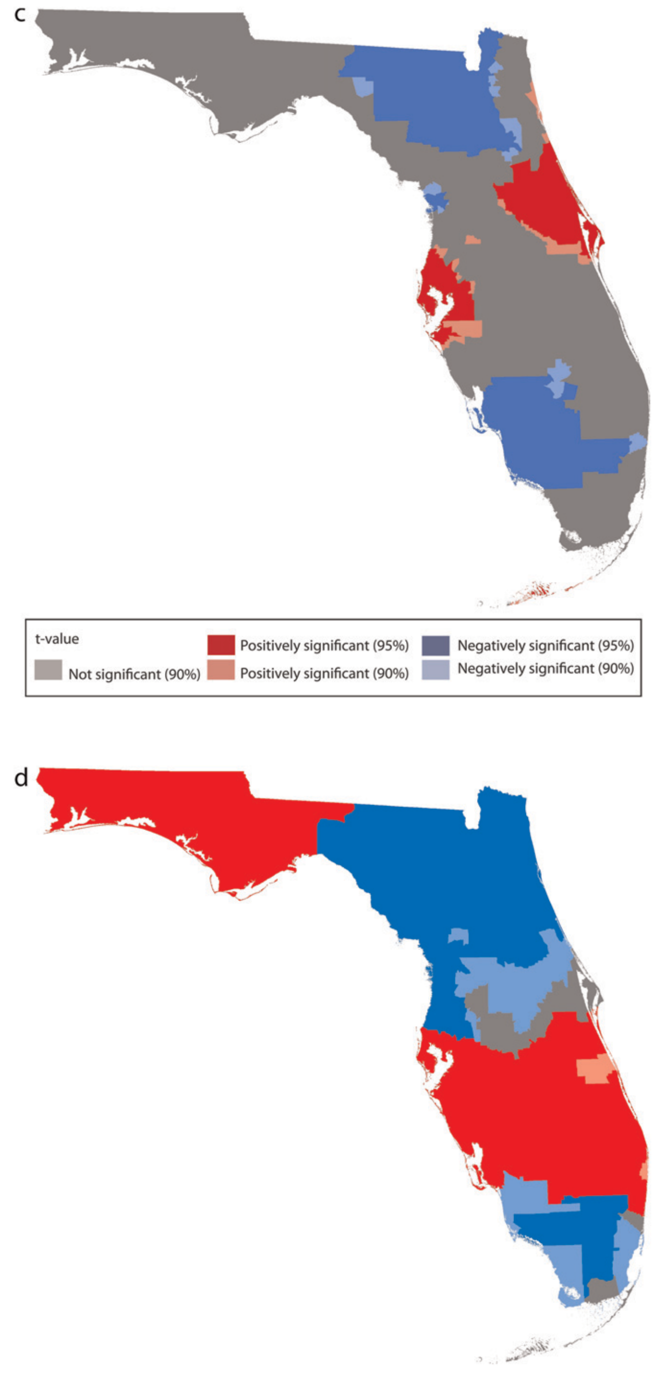

FIGURE 4—(Continued).

and assist researchers in developing new analytical techniques that address limitations of conventional approaches.

Current methodological and data deficiencies may be mitigated by providing more targeted funding to correct some of these problems and ensure that future EJ research is not constrained by such limitations. This funding would lead to more reliable results, stronger evidence, and improved understanding of the relationships among hazard proximity, exposure, and health disparities, as well as better solutions to environmental health injustices. ■

About the Authors

Jayajit Chakraborty is with the Department of Geography, University of South Florida, Tampa. Juliana A. Maantay is with the Department of Environmental, Geographic, and Geological Sciences, Lehman College, City University of New York. Jean D. Brender is with the Department of Epidemiology and Biostatistics, School of Rural Public Health, Texas A&M Health Science Center, College Station.

Correspondence should be sent to Jayajit Chakraborty, PhD, Department of Geography, University of South Florida, 4202 East Fowler Avenue, NES 107, Tampa, FL 33620 (e-mail: jchakrab@usf.edu). Reprints can be ordered at http://www.ajph.org by clicking the "Reprints/Eprints" link.

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Contributors

J. Chakraborty, J. A. Maantay, and J. D. Brender conceptualized the analytic review. J. Chakraborty and J. A. Maantay compiled the systematic review of the literature and shared supervision of the article's overall content. J. D. Brender reviewed the manuscript of the article and contributed to the conclusions and recommendations.

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