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Scales of environmental justice: Combining GIS and spatial analysis for air toxics in West Oakland, California

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Abstract

This paper examines the spatial point pattern of industrial toxic substances and the associated environmental justice implications in the San Francisco Bay Area, California, USA. Using a spatial analysis method called Ripley's *K* we assess environmental justice across multiple spatial scales, and we verify and quantify the West Oakland neighborhood as an environmental justice site as designated by the US Environmental Protection Agency. Further, we integrate the ISCST3 air dispersion model with Geographic Information Systems (GIS) to identify the number of people potentially affected by a particular facility, and engage the problem of non-point sources of diesel emissions with an analysis of the street network.

Keywords: Environmental justice; GIS; Point pattern analysis; Ripley's *K*; West Oakland

Introduction

Environmental justice theory

Environmental injustice has multiple meanings to different people, but can be thought of simply as occurring when a particular social group is disproportionately burdened with environmental hazards (Pellow, 2000). Pellow defines environmental racism, an environmental justice issue, as the institutional rules, regulations, and policies of government or corporate decisions that deliberately target certain communities for least desirable land uses, resulting in the disproportionate exposure of toxic and hazardous waste on communities. Environmental inequality addresses structural questions that focus on social inequality of power, resources and environmental burdens.

Environmental justice cases in California have focused recently on air pollution exposure from urban traffic (Houston et al., 2004), especially with regards to public schools (Morello-Frosch et al., 2002b; Pastor et al., 2002), and public policy for health risk measurements (Dunsby, 2004). Additionally, environmental justice has been addressed in California's water management (Haughton, 1998), Toxic Releases Inventory (TRI; volume and location of emissions from facilities), and treatment, storage, and disposal facilities (TSDF), though the geographic focus has been primarily on Southern California and Los Angeles rather than the San Francisco Bay Area (Morello-Frosch et al., 2002a; Sadd et al., 1999; Boer et al., 1997; Morello-Frosch

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et al., 2001). The US Environmental Protection Agency's (US EPA) Air Toxics and Environmental Justice teams at the Region 9 Office recently focused their assessment of justice and equality on the health impacts of air toxics on a dense minority and low-income area in West Oakland, California in the San Francisco Bay Area through a sequence of events. Citizens suspected that their health was at risk from odorous releases from the many facilities in the area. Additionally, heavy diesel truck (vehicular) traffic was increasingly becoming a problem due to truck routes through their residential neighborhood (Pacific Institute and Coalition for West Oakland Revitalization, 2003). The community of West Oakland mobilized (for mobilization on a transit issue, see Rodriguez, 1999) and approached the US EPA for help.

A working relationship does not in itself push a community to the top of the US EPA list. Two additional factors made West Oakland a top priority: an unusually high number of pollutant sources and a high density of minority and low-income people, all of which were matters of high public awareness in the region. On this base of perception, there was then need for valid empirical demonstration of congruent clustering of emissions and of minority residential populations. The agency needed to know the numbers of pollutant sources and the population structure in West Oakland before designating this area for priority attention.

We analyzed environmental justice in West Oakland across multiple scales with a point pattern analysis of spatial statistics new to environmental justice. Our objectives were to pinpoint statistically significant clusters of point source polluters and examine the surrounding demographics. Through Geographic Information Systems (GIS) we investigated non-point source pollution in addition to estimating the demographics affected by the most dangerous point-source polluter via a Gaussian plume model. The purpose of this research was to answer and quantify questions of scale in environmental justice.

The underlying processes that lead to environmental injustices can be political, economic, historical, and social. Politically, this could be lack of representation or participation, lack of lobbying power, greed among politicians, NIMBYism (not in my backyard), unequal power in the legal system and inadequate laws (Cole, 1992), zoning (Maantay, 2001), and inadequate regulations/enforcement/permitting (Levenstein and Wooding, 1998; Weinberg, 1999; Mank, 1999). Economic processes include suburban sprawl (Ellis et al., 2002), widening income gaps (Krugman, 2002), capitalism externalities (Levenstein and Wooding, 1998), and market dynamics (Been, 1994). Historical processes vary for different peoples, but these might include slavery, Jim Crow laws,[1] land ownership (Romm, 2000), disenfranchisement, persecution, anti-immigrant laws, genocide, access to health care (US Commission on Civil Rights, 2003), and immigrant work programs (Marentes, 2004). Social processes include stereotypes (Bobo, 2001), racism (Pulido, 1996), language barriers, segregation, hegemony, social construction, affirmative inaction and mismatched attitudes (Blackwell et al., 2002).

Critics of environmental justice have cited methodological problems (Friedman, 2003; Oakes et al., 1996; Yandle and Burton, 1996), alternative causal interpretations such as market dynamics of capitalism (Been, 1994), and misplaced priorities such as poverty over pollution (Foreman, 1998). Further, it has been argued that potentially hazardous industries would provide compensation such as jobs for minorities and that increased wealth leads to increased health benefits (Tiebout, 1956; Adler, 1999; Simon, 2000), but these arguments neglect the scale at which wealth and health benefits relate to the detrimentally affected local people. Facilities may not employ local residents nor pay an equitable wage (Pellow, 2000). Further, even if facilities are not directly polluting, accidents can occur (Bolin et al., 2000).

Legislatively, environmental justice in the US is addressed in a number of media. The 14th Amendment mandates equal protection under law, but intent must be shown to prove discrimination (such as clearly selective enforcement, unequal municipal services, or statements by government officials). Title VI of the Civil Rights Act prohibits discrimination by Federally funded programs, and the Supreme Court requires intent to be shown if a lawsuit is brought under Section 601, yet only disparate impact for administrative complaints under Section 602 (Weinberg, 1999; Mank, 1999). Disparate impact may be evaluated through five steps (Mank, 1999): (1) Identify the affected

[1]Jim Crow laws were part of anti-African American legislation passed in the Southern states after the American Civil War. Examples include attendance in public schools and the use of facilities such as restaurants, theaters, hotels, cinemas and public baths. Trains and buses were segregated and interracial marriage was outlawed.

population, especially those in close proximity to the facility; (2) Determine the demographics of the affected population through mapping technology such as GIS; (3) Determine the universe(s) of facilities and total affected population(s), especially the cumulative pollution burden of neighboring facilities; (4) Conduct a disparate impact analysis both by examining the racial or ethnic composition within the affected population and by comparing that composition to unaffected populations in other relevant areas; (5) Determine the significance of the disparity through the use of standard statistical methods. We follow the steps outlined above in this research.

The US EPA historically has failed to enforce Title VI because of conflicts with the agency's primary goal to reduce pollution (Mank, 1999). In 1994, President Clinton issued Executive Order 12898, which mandated all Federal agencies to address environmental justice in minority and low-income populations. Although the US EPA created an Office of Environmental Justice for guidance (US Environmental Protection Agency, 1992, 1998), the Office of Inspector General[2] released a review report stating that the US EPA had not been consistently implementing the intent of the Executive Order (Office of Inspector General, 2004). Among the Office of Inspector General's findings were that the US EPA had recently de-emphasized minority and low-income populations in environmental justice, and that the methods of analysis, including the use of GIS, had been inconsistent. The US EPA must follow a methodology by which disparate impact can be assessed, and populations can be analyzed appropriately and consistently.

Spatial analyses of environmental justice

In this paper we apply a point pattern statistical approach to environmental justice research that avoids pre-determined units of analysis to identify appropriate scales of analysis. A number of studies have integrated point pattern analysis into a GIS framework and have explored the value of this approach to epidemiology (Gatrell and Bailey, 1996; Kingham et al., 1995) in the context of detecting clusters (Bhopal et al., 1992; Fotheringham and Zhan, 1996; Gatrell et al., 1996). Our spatial point pattern analysis is based on Ripley's K-function (Ripley, 1976), which has been broadly applied in ecological spatial patterns; examples include landscape dynamics of forest disease (Kelly and Meentemeyer, 2002), distribution patterns of herbs (Kenkel, 1993), desert shrubs (Prentice and Werger, 1985; Skarpe, 1991), and tropical forest trees (Sterner et al., 1986). O'Brien et al. (1999) used Ripley's K to assess the spatial and temporal distribution of canine cancers in Michigan. Barff (1987) analyzed the second-order point pattern of manufacturing plants in Ohio for economic and social justice.

Ripley's K examines the test statistic across various spatial scales and reveals the scale at which the pattern of events is operating most strongly. Furthermore, our analysis avoids the use of census tracts,[3] which are politically defined and can change with time. Ripley's K addresses the distributive theory of equality in questioning whether or not certain communities are burdened with a disproportionate number of facilities. Not only does the statistic provide agencies such as the US EPA with sound backing of statistical significance and a link to equality and justice theory, but it also helps guide policies at the appropriate political-spatial scale—from international, national, and regional/state to county, city, and neighborhood.

Initial studies in environmental justice showed that emissions are concentrated in minority relative to predominantly white residential areas, with consequently differential health impacts among racial groups (United Church of Christ Commission on Racial Justice, 1987; Bullard, 1994). However, critics were quick to point out flaws in the analysis with emphasis on scale—results and conclusions can change depending on the range of space and time analyzed (Anderton et al., 1994; Friedman, 2003). Maantay (2002) reported that there is a need to develop more accurate methods for determining the geographic extent of exposure and the characteristics of the affected populations, to use dispersion modeling and advanced proximity analysis, and

[2]The Office of Inspector General is an independent office within EPA that audits, evaluates, and investigates the EPA to promote economy and efficiency, and to prevent and detect fraud, waste, and abuse (http://www.epa.gov/oigearth).

[3]A census tract, as defined by the U.S. Census Bureau, is a statistical subdivision of a county delineated by a local committee of census data users for the purpose of presenting data. Census tract boundaries normally follow visible features, but may follow governmental unit boundaries and other non-visible features. They are designed to be relatively homogeneous units with respect to population characteristics, economic status, and living conditions at the time of establishment, and average about 4000 inhabitants.

neighborhood-scale analysis. Rhodes (2003) suggested the use of several different spatial measurement units with geographic problems and to be sensitive if or when the indications of environmental justice problems change. We implement the conclusions of these researchers here, with particular attention to varying spatial scale, neighborhood-level analysis and dispersion modeling.

The standard spatial scale of analysis for environmental justice with GIS in the US has been the census tract level (Bowen et al., 1995; Szasz and Meuser, 2000; Cutter et al., 2002; Buzzelli et al., 2003; Yandle and Burton, 1996). The focus on the census tract assumes that point sources and the population are distributed uniformly throughout the census tracts, which are inconsistent in size and shape. Researchers have attempted to avoid the census tract level with proximity-based assessments of demographics within a certain radius of a given facility. The exact radius is often fitted, subjective, or arbitrary (Anderton et al., 1994), however, and should depend on air movement. Radius sizes have ranged from 0.5 km (Dunn et al., 1995, 2001; Dunn and Kingham, 1995), 0.8 km (Baden and Coursey, 2002), and 1.6 km (Glickman and Hersh, 1995; Bolin et al., 2000), to 4.0 km (Anderton et al., 1994); Pastor et al. (2004) examined a range of 0.8, 1.6, and 4 km buffers. Additionally, these authors employed a range of statistical tests, such as χ^2, Cramer's V (Cramér, 1999), raised incidence modeling (Diggle and Rowlingson, 1994), and the Townsend index of deprivation (Townsend et al., 1988). Some authors were content with producing maps with no statistics.

Scholars have debated what the unit of analysis should be, from the "community" that is based on census block groups and travel time (Taquino et al., 2002) to raster-based (Mennis, 2002) or multi-scalar analysis (Williams, 1999). There has also been criticism that the choice of target predetermines the evaluation of social impact. We take a different path: scale becomes a variable rather than a predetermined measure. We seek to identify the scales at which clusters, and congruence among them, are more and less likely to exist for different analytical purposes.

Methods

Data

The main demographic information (e.g. population density, race breakdown) was obtained from the US Census Bureau's 2000 survey at census tract, block group, and block spatial scales. We used TRI for 1999 (to compare to the 2000 Census data) for the point pattern analysis.[4] The annual TRI records the volume and location of self-reported releases from private sector and federal facilities. All industries that meet the following criteria have mandatory reporting: (a) the production facility's primary standard industrial classification is manufacturing; (b) the facility has 10 or more full-time employees; and (c) the facility manufactures or processes over 25,000 pounds of at least one of the over 600 TRI chemicals, or uses more than 10,000 pounds of at least one TRI chemical (US Environmental Protection Agency, 1997; US General Accounting Office, 1991a, b). Specifically, TRI chemicals in West Oakland included: chlorine, chromium, nitrate compounds, and zinc compounds, though the carcinogen acetaldehyde is perhaps the most harmful. Data are provided for each release medium, including air, water, underground injection, land, and off-site transfers. A critical methodological issue is the accuracy of the locations of point-source hazards found in US EPA data sets (e.g., Scott et al., 1997; Stockwell et al., 1993; Glickman and Hersh, 1995). But, the US EPA TRI data offers the most comprehensive measures of industrially released hazardous emissions in the United States, particularly after we checked for locational validity by geocoding each TRI location to its correct street address (Bolin et al., 2000; Daniels and Friedman, 1999; Krieg, 1998b; Mitchell et al., 1999). Addresses used in geocoding were verified as the facility address rather than the office address.

The BAAQMD health risk screening was based on the US EPA's Industrial Source Complex Short Term (ISCST3) air dispersion model (US Environmental Protection Agency, 1995, 1999), and those risks were estimated in accordance with procedures adopted by Cal/EPA's Office of Environmental Health Hazard Assessment (OEHHA) for the Air Toxics Hot Spots Program. The ISCST3 model has been validated successfully for a number of pollutants in a variety of locations (e.g., Lorber et al.,

[4]Additional data reviewed for West Oakland, but not used in the point pattern analysis: US EPA Region 9 Air Division's Air Quality System (formerly named the Aeromatic Information Retrieval System or AIRS); National Pollutant Discharge System (NPDS); sources listed under the Resource Conservation and Recovery Act (RCRA); and a yellow pages listing for gasoline stations.

2000; Kumar et al., 1999; Mazzeo and Venegas, 2004; Elbir, 2002). Dispersion is a term that describes advection (horizontal movement) and diffusion (mixing) of gases. Air dispersion models can range from simple models that require minor computation to complex three-dimensional models that require extensive data and computation, the type of which depends on the scale of the problem and the input data available. Chakraborty and Armstrong (1995) detail the methodology by which to determine demographic composition of a population affected by the release of toxic substances. They describe the Geographic Plume Analysis approach that takes a dispersion model, which outputs a dispersal "footprint", and superimposes it on a demographic database. We follow this approach here.

The data were processed in a GIS database containing air pollutant source data (US Environmental Protection Agency, 1997) for US EPA Region 9 (Arizona, California, Nevada and the Pacific Islands) and detailed demographic information for West Oakland from the 2000 US Census (US Bureau of the Census, 2000). We integrated the database with *S-Plus* 6.0 and ESRI's *ArcGIS* 8.1. The main statistical processing of point pattern analyses relied on *S-Plus* 6.0, and analyses and map production on the *ArcMap* component of *ArcGIS* 8.1. The data were projected into Albers Equal Area with the North American Datum 1983 to preserve area measurements.

Analysis

Clusters of point source polluters were identified through point pattern analysis that combined intensity distributions and Ripley's *K*. Intensity is defined as the mean number of points per unit area; intensity distributions reveal first-order properties of a spatial point process and variation through space to assess the spatial dependence between points. First-order properties of a spatial point process describe how the mean number of points per unit area (the intensity) varies through space. For a stationary process, the intensity is assumed to be constant over the bounded region of interest. We initially followed a weighted edge correction (Ripley, 1977), though Lancaster and Downes (2004) specify that edge correction is not necessary for length-scale assessment of clusters. Intensity distributions show *where* clusters are occurring, Ripley's *K* reveals *statistical significance* of those apparent clusters.

Ripley's *K* is a second-order (variance of distances) function for spatial point pattern and is used to detect spatial randomness (Ripley, 1976). A spatial point pattern is a collection of points irregularly located within a bounded region of space (e.g. pollutant sources within a county). The data set may consist of locations only, or it may be a marked point process, with data values associated with each location (e.g. longitude/latitude with associated emissions). The analysis is termed "second-order" because of its focus on the variance of the test statistic across a series of progressively larger areas—the size of the step is set to reveal the inter-event distances at which clustering, if present, is strongest. By examining the test statistic at various spatial scales (e.g. region, county, city), the scale at which the pattern of events (points) is operating most strongly (highest statistical significance and confidence) can be determined. Ripley's *K* examines the null hypothesis of complete spatial randomness (CSR) for a mapped spatial point pattern. CSR is defined by the following criteria: (a) the intensity of the point pattern does not vary over the bounded sampling region, and the pattern follows a homogeneous Poisson distribution; (b) there are no interactions among the points. Ripley's *K* can reject the null hypothesis that the spatial pattern of points is random.

After the data were analyzed by the Ripley's *K* method, a plot of count $K(h)$ versus distance h revealed deviations as expected under CSR. The deviation was tested for statistical significance. One test employed the calculation of constant approximate confidence intervals around CSR (Getis and Franklin, 1987; Szwagrzyk and Czerwczak, 1993). Another test used Monte Carlo methods to determine statistical significance of the results by determining the amount of variation to be expected in sample statistics from computer-generated data (e.g., Manly, 1991). In the context of spatial pattern analysis, Monte Carlo methods simulate randomly generated plots of the same dimensions of the observed plot thus creating confidence intervals from the highest and lowest values of $K(h)$ (Haase, 1995). We plot $((K(h)/\pi)^{0.5}–h)$ or simply $(L(h)–h)$ against h to show the deviation of $K(h)$ from CSR. If the deviation of the sample statistic from zero expectation is positive and above the upper limit of the confidence interval, then a clumped distribution can be assumed, while negative deviation indicates a regular pattern, otherwise the null hypothesis of CSR cannot be rejected (Haase, 1995).

Our GIS analysis followed the point pattern analysis with an examination of the communities and pollutant sources in the proximity of identified clusters of point source polluters. We determined race and income distributions in addition to the presence or absence of environmental goods (e.g., parks). With the BAAQMD health risk screening based on the US EPA's ISCST3 air dispersion model, we evaluated in the West Oakland cluster the potential exposure by the facility Red Star Yeast (LaSaffre Yeast Corp., a division of Universal Food Corp.), which the US EPA determined posed the greatest health risk due to carcinogenic emissions of acetaldehyde (personal communication Grow, 2001). LaSaffre Yeast Corp., which operates in over 180 countries, ranked 8th of all San Francisco Bay Area facilities for cancer health risks, and 2nd in Oakland for air pollution health risks (Greenaction.org, 2003). From an environmental justice standpoint, Red Star Yeast was situated not in a wealthy community of political influence and control, but in poor community with little power to defend itself from injustice. Finally, we assessed mobile source pollution with an examination of the road network and travel routes within and around the neighborhood.

Results

First- and second-order spatial analysis

An initial examination of point sources in the US EPA's Region 9 in California shows clusters unsurprisingly in the major population centers of the San Francisco Bay Area and Los Angeles. With the question of West Oakland in mind, we first analyzed all TRI sources from 1999 in the San Francisco Bay Area cluster, which includes the counties of Alameda, Contra Costa, Marin, San Mateo and San Francisco (Fig. 1a). An intensity distribution revealed multiple peaks, with the two largest clusters located in the East Bay (Fig. 1b). Our Ripley's K test found that the two major clusters were statistically significant whereby the deviation of the sample statistic from zero expectation was positive and above the confidence interval (Fig. 1c). The distribution of Ripley's K above the upper confidence interval indicates clustering, between the confidence intervals indicates random spatial pattern, and below the lower confidence interval indicates a regularly distributed pattern. The y-axis represents the deviation of the sample statistic from CSR; the units are in count numbers, but have been transformed as per Haase (1995). The x-axis represents distance (units are in degrees of longitude and latitude here), and the distance shows the extent of the clustering.

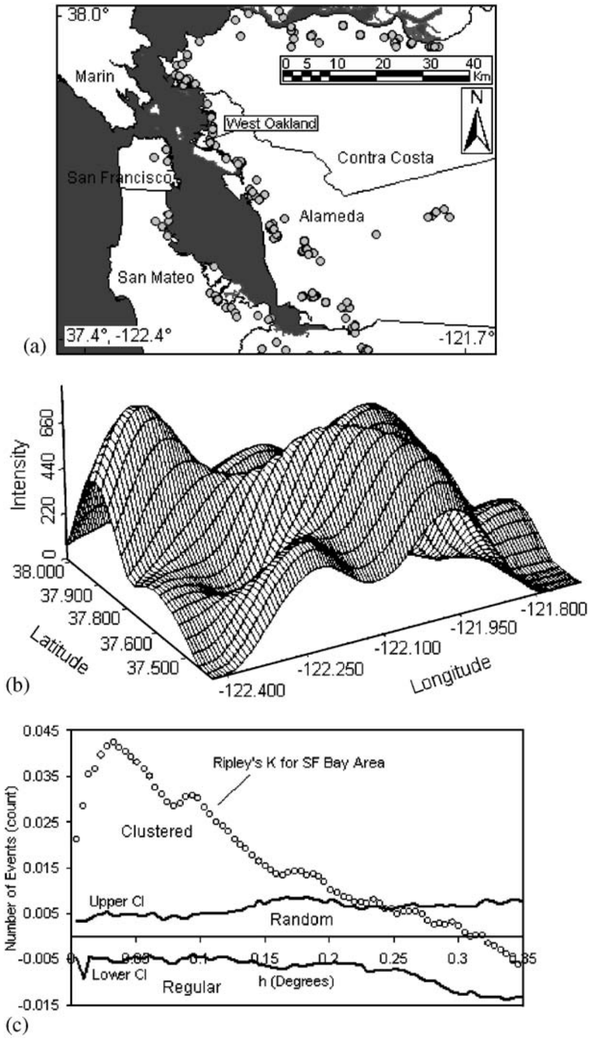


Fig. 1. (a) TRI (1999) facilities in the San Francisco Bay Area. (b) Intensity distribution for TRI (1999) sources in the San Francisco Bay Area of points per grid cell in longitude by latitude. (c) Ripley's K test for TRI (1999) facilities in the San Francisco Bay Area. The distribution above the upper confidence interval indicates clustering at the scales of degrees. The distribution between the confidence intervals indicates a random spatial pattern. Below the lower confidence interval would indicate a regular spatial pattern. The y-axis represents the deviation of the sample statistic from CSR; the units are in transformed count numbers. The x-axis represents distance (units are in degrees here.

Second, we examined the East Bay (Alameda County) TRI clusters specifically, again with the

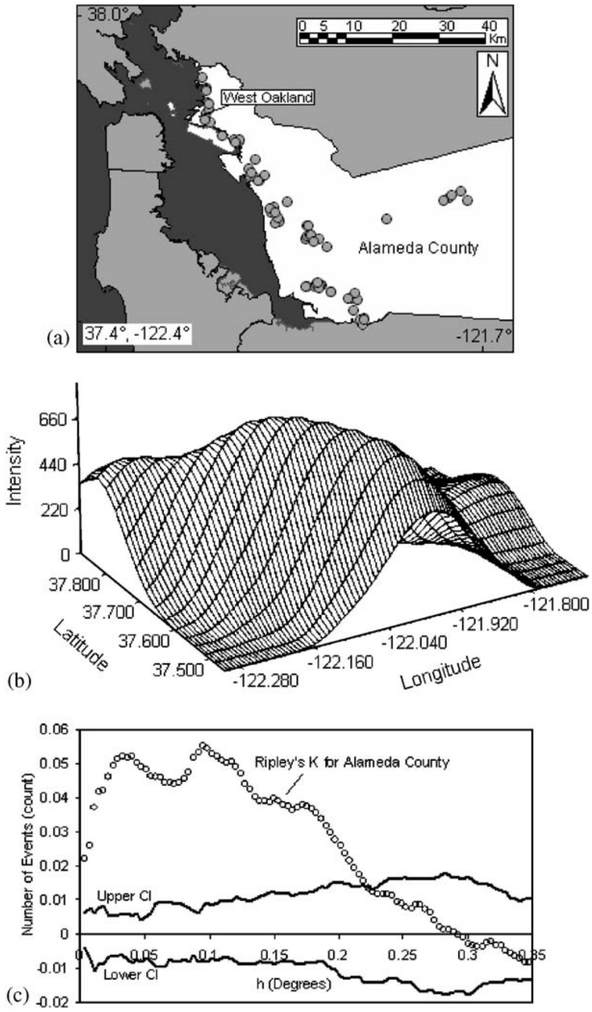


Fig. 2. (a) TRI (1999) facilities in Alameda County. (b) Intensity distribution for TRI (1999) facilities in Alameda County. (c) Ripley's K test for TRI (1999) facilities in Alameda County.

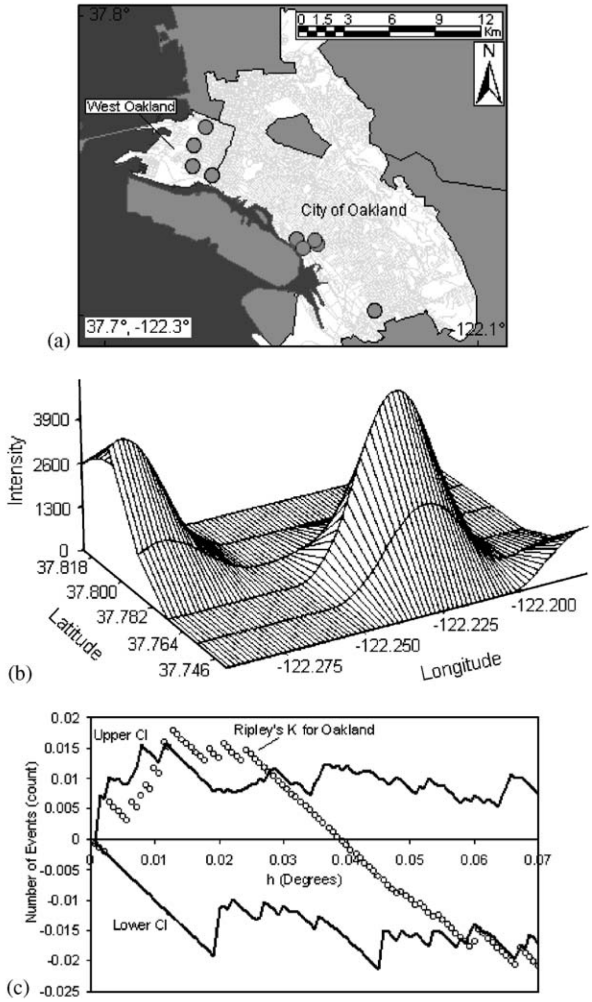


Fig. 3. (a) TRI (1999) facilities in the City of Oakland. (b) Intensity distribution for TRI (1999) facilities in the City of Oakland. (c) Ripley's K test for TRI (1999) facilities in the City of Oakland.

intensity distribution and Ripley's K (Figs. 2a–c). The intensity distribution shows the evident positioning of facilities along the west side, but cannot distinguish clearly individual clusters within that swell of facilities. We were able to distinguish the individual clusters within that swell with the Ripley's K plot as evidenced by the three peaks in the clustered area of the plot (Fig. 2a). Because the US EPA was interested in validating the identification of West Oakland as an environmental justice site, we examined in depth the City of Oakland cluster (Fig. 3a). The intensity distribution illustrates the two clusters of facilities, but cannot determine if those peaks are statistically significant clusters (Fig. 3b). The Ripley's K plot shows that there is still statistically significant clustering occurring, though the data have become limited at this small of a spatial scale so this is the smallest scale at which we can examine with Ripley's K (Fig. 3c).

GIS analysis for West Oakland

After determining the presence, scale, and location of clusters, the next step in an environmental justice framework is to examine the communities within the extent of those clusters. Using the US Census Bureau 2000 survey, we analyzed the block level data (a block is roughly equal to a city block) for the cluster at West Oakland. The greatest density of West Oakland residents is situated in the center and along the eastern freeway border of

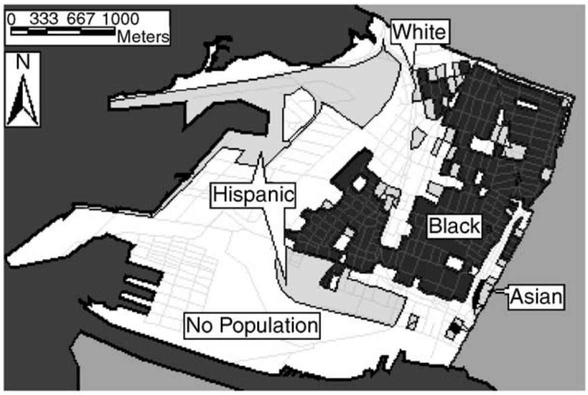


Fig. 4. Broad race distribution map based on racial majority for each block in West Oakland.

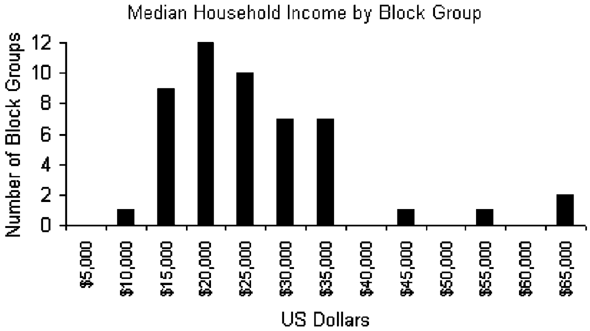


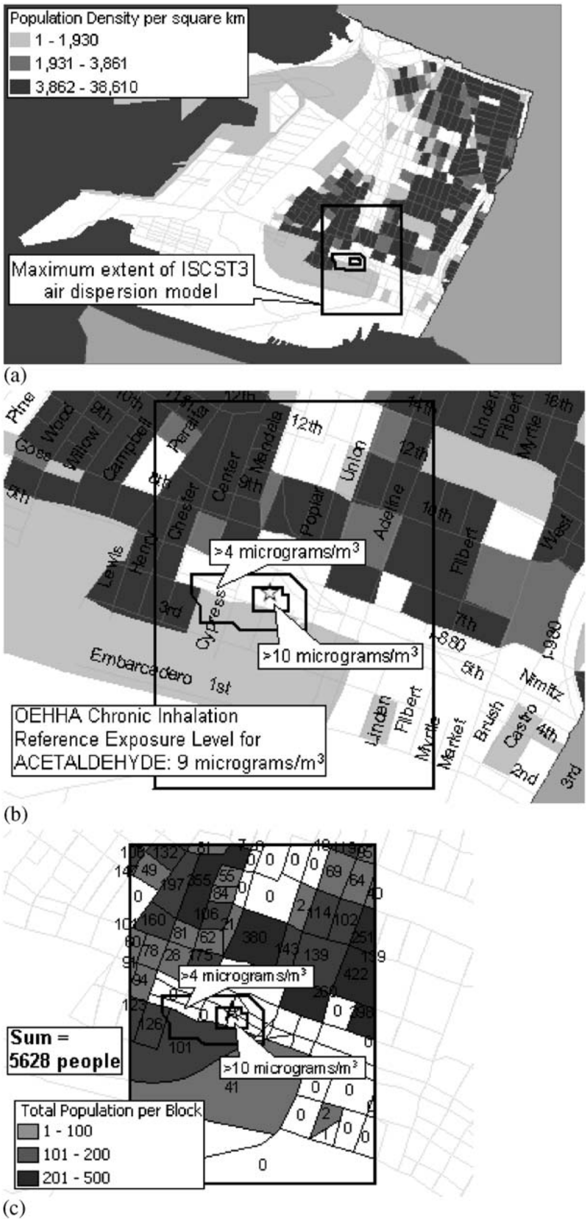
Fig. 5. Median household income by block group (frequency) in US Dollars.

the area; the western industrial port is largely uninhabited. We created a broad race distribution map based on the racial majority for each block (Fig. 4). This map shows that the majority of the West Oakland community is African American. In West Oakland, African Americans (Black) comprise 65% of the population, the rest of the population is made up of Caucasians (White; 9%), Latinos (Hispanic; 7%), Asians (9%), and "Other" (racial mixes, Native Americans/American Indians, Hawaiian; 10%). The median household income per year is roughly $20–25,000US, which is lower than that of the surrounding areas (Fig. 5). There are 14 schools in West Oakland, half of which are within 600 m of a TRI facility. There are some parks (an environmental good), but the newest one is rarely used as it is adjacent to the freeway and a Superfund site.[5] There are no hospitals in West Oakland.

We split air pollutant sources into stationary (e.g. factories) and mobile (e.g. vehicles) sources. Stationary sources are scattered throughout West Oakland, but they are not equal to each other in their relative health threat to the community. Now, from a TRI database with thousands of facilities the US EPA can focus on the facilities that pose the greatest health threats—in the case of West Oakland, the carcinogenic emissions of acetaldehyde by Red Star Yeast. We integrated the BAAQMD air modeling analysis of Red Star Yeast's emissions into the GIS (Figs. 6a and b). We overlaid the ISCST3 air dispersion model on top of the block level population layer in order to determine the number of people potentially affected by Red Star Yeast (Fig. 6c). The resulting estimate of 5628 people is derived from the maximum extent of the BAAQMD model, including the whole of those blocks cut by the model, but the number of people who live within the high-concentration areas is under 268. Furthermore, the air dispersion model is drawn in much more detail closer to the facility, whereas uncertainty leads to a generalized rough rectangle for the maximum bounds. The highest concentrations of acetaldehyde emitted from the facility effect those populations living closest to Red Star Yeast, and the associated health effects are subject to the assumptions of the model. Here, we found the estimated number of people potentially exposed to Red Star Yeast's emissions based on the block level demographic information within the boundaries of the ISCST3 model.

The mobile source in West Oakland is primarily from heavy diesel truck traffic through the community to the Port of Oakland. Chemicals in diesel pollution may cause cancer, harm the reproductive system and aggravate asthma (Morgan et al., 1997; Kagawa, 2002). The Pacific Institute and Coalition for West Oakland Revitalization (2003) offered a number of ideas to alleviate these problems. With GIS we assess two of their recommendations: install traffic barriers on prohibited streets, and create a designated truck route not through the neighborhood. As communicated by the US EPA, the truck drivers indicated that there are only a few gasoline (petrol) stations near the port and those stations are unavoidably in the middle of the densely populated neighborhoods (personal communication Grow, 2001). We mapped the population density, road

[5]A Superfund site is any land in the US that has been contaminated by hazardous waste and identified by the EPA as a candidate for cleanup because it poses a risk to human health and/or the environment (http://www.epa.gov/superfund/).



Figs. 6. (a) and (b) Extent of Red Star Yeast emissions based on BAAQMD's Health Risk Screening Analysis on population density per square mile. (c) Total number of people potentially affected by Red Star Yeast emissions.

network, port terminals, and all gasoline stations (15) within a 2.4-km (1.5-mile) radius of the center of West Oakland along with the major terminals (Fig. 7). Based on the two recommendations and Fig. 7, we found an alternative-driving route around the high population density. The roads currently used—which cut through the community—are crossed off with X's, and the alternative route is highlighted. In sum, the key results here are: (1) detection of the cause of the problem—the three roads that run into the community; and (2) recommendation of a solution to the problem—an alternative route around the community. Without site familiarity, the US EPA would have little sense of road spacing and gasoline station locations. The GIS can provide a clear picture to the arguments posed by the residents and truckers on transit routes and gasoline stations.

Discussion

We used Ripley's *K* combined with GIS to identify not only statistically significant areas of clusters, but also the scales at which those clusters exist. This research focused on narrowing down the extensive region- and state-wide datasets into local neighborhoods that can be applied with local remedies. It is not unusual that a hierarchy of politics and economics exists across spatial scales for environmental justice (Simmons, 2004). At the local level, new issues emerge that may not otherwise be evident at larger scales, such as the road network and transportation problem. Corrective justice, which is the notion that polluters should be punished and held responsible for cleanups and should compensate or repair communities damaged by historic pollution, can be implemented at the local level (Lazarus, 1993). But, intermediate scales of clusters were also seen in, for example, the clustering of facilities in the East Bay relative to the San Francisco Bay Area as a whole. We focused on West Oakland not only as a directly applicable problem, but also as a means to raise and answer broader questions and purposes to be applied generally.

As the spatial scale becomes smaller we necessarily lose the amount of data points to work with and the analysis and interpretation of the intensity distributions and Ripley's *K* plots likewise changes. At the scale of the San Francisco Bay Area, clustering is most dominant in the East Bay, though geography influences clustering and edge effects as well (water and topography constrain potential sites at this scale that play less of a role at other sites and scales). The intensity distribution can show where clumping occurs, but the largest peaks are likely the most important clusters because the peaks are based on a scale relative to one another. At the scale of Alameda County, the intensity distribution reveals little about individual clustering, as it seems that the

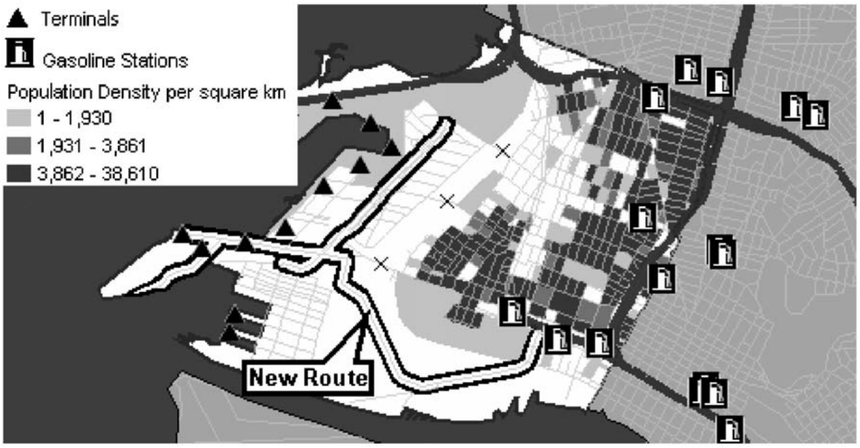


Fig. 7. Road network, port terminals, gasoline stations, and an alternative-driving route around the high population density.

point sources are evenly spread along the water (large peak on the west side). The Ripley's K plot, however, is more informative at the county scale where geography and edge effects are minimized. Three clear peaks in the plot point to three areas of clusters all within the broad cluster along the water. Analysis of one of those three peaks—the City of Oakland—shows two areas where facilities are located. The intensity distribution shows a cluster where West Oakland is defined, and another more intense peak (the facilities are clustered closer together) further south. The Ripley's K plot is not as clear at this scale because the data have become so sparse relative to the larger scales.

As with other EPA hazard data, there are recognized limitations to the TRI data. In addition to not providing human exposure information, the data are restricted to large manufacturing facilities and exclude releases from smaller firms, landfills and abandoned industrial sites, hazardous waste facilities, and power plants (Bolin et al., 2000). Pastor et al. (2004) report that it is difficult to make time series or longitudinal comparisons in TRI emission reporting due to periodic changes in the reporting requirements, but this paper focuses primarily on issues of spatial scale. Further epidemiological work is still needed.

The literature on GIS and spatial analysis for environmental justice has focused on census tracts or proximity-based assessments within variable radii from facilities. Critics have argued the need to assess environmental justice across different spatial scales; additionally, dispersion modeling and neighborhood-scale analysis has been called for (e.g., Maantay, 2002). Further, no clear consensus on appropriate spatial statistics has emerged, because each statistic addresses different types of questions. We add to the environmental justice literature a method that: (1) avoids census tracts and radii-based proximity assessments; (2) assesses environmental justice across large and small spatial scales; (3) integrates a well-developed air dispersion model with demographic data; and (4) includes a measure of statistical significance for cluster evaluation.

The Office of Inspector General criticized the US EPA's de-emphasis of minority and low-income populations in addressing Executive Order 12898. While the criticism is certainly justified, the US EPA must grapple with changing political power and administrative changes that lead to these shifts in emphasis. The method we present here approaches the issue of environmental justice without starting with race or income, since such a starting point might lead to bias in data interpretation. In other words, our results showed that clusters of polluters are statistically pinpointed first, and then the surrounding demographics are examined next rather than the other way around. Unfortunately, minorities and low-income populations are often coupled with these clusters nonetheless, hence the rationale behind the environmental justice movement, though certainly many minorities and poor people live in clean environments.

This analysis also ties into "disparate impact" as was discussed on Section 602 in Title VI of the Civil Rights Act. Disparate impact is now connected to communities living within statistically significant clusters, or a disparate number of TRI facilities relative to other communities. The US EPA can apply these results to implement policies, but based on what notions of justice or equality? Theories of justice (Rawls, 1999; Miller, 1999; Wenz, 1988) range from utilitarian (greatest good for greatest number), libertarian (greatest individual benefits without harm), communitarian (community over individual), and egalitarian (greatest benefit to least advantaged—maximize the minimum). Theories of equality (Sharder-Frechette, 2002) include distributive justice (equal apportionment of social benefits and burdens), participative justice (equal rights to self-determination in societal decision-making), and procedural justice (equal distribution of enforcement, monitoring and other processes).

Some theories of justice and equality simply are insufficient to base policies on. A utilitarian approach, for instance, might justify disproportionate environmental burdens if society as a whole is better off economically due to production, but Lejano et al. (2002) has already found that there is no justice in this approach, at least for air quality policies in Southern California. Procedural justice has been argued as insufficient in the environmental justice in California and the Southwestern US to advance environmental equality (Pulido, 1994). Although the State of California's EPA has emphasized participative justice in environmental justice policies (California Environmental Protection Agency, 2003), this may be more difficult to apply at a federal level for the US EPA. Other theories of justice and equality need to be reinforced through policies. The egalitarian approach is lacking because West Oakland, considered as the least advantaged in terms of income, exposure to pollution and access to environmental goods, is not realizing the greatest benefits. The US EPA must implement distributive justice because these social burdens are not equally apportioned.

Areas like West Oakland may be obvious areas for targeting environmental justice research due to the high amounts of pollution coupled with high minority concentrations, and the communities mobilized to solve their local injustice found there. For future inquiry, however, other communities may be less mobilized and empowered or the clustering of pollutant sources may be less obvious than those studied here. Although the spatial data analysis techniques were used to verify existing environmental justice areas, these methods can be used to identify new areas for study relatively quickly and efficiently. The creation of potential environmental injustice areas may be proactively avoided if the US EPA has an efficient data-monitoring strategy whereby clusters of possible polluters would trigger a statistical alarm. Certainly, not every cluster would necessarily be an environmental justice site, but this would at least provide a mechanism for the US EPA to focus their efforts for further research. Additionally, if the air dispersion model can be applied to many facilities simultaneously, then a possible aggregate impact could be assessed. It is important that the US EPA continue to use GIS and spatial data analysis to approach these issues and expedite the process to the enforcement stage.

Following the completion of this analysis (but before publication), the US EPA applied our results in combination with community members, activist groups,[6] and Federal, State and local agencies to apply pressure on Red Star Yeast to significantly restrict emissions or face sanctions and be shut down. Further, BAAQMD did not renew Red Star Yeast's air emissions permit. Subsequently, Red Star Yeast announced that they would close their facility in West Oakland due to "market conditions" and "challenging California environmental conditions." From an environmental justice standpoint for the community, the closure was a victory that came from activism, science, and involvement with government agencies.

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[6]The activist groups included: Chester Street block Club Association, Citizens for West Oakland Revitalization, Environmental Science Institute, Greenaction for Health and Environmental Justice, Pacific Institute, and Youth Empowerment Center.

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