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## Environmental Racial Inequality in Detroit

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### Abstract

This study uses industrial pollution data from the Environmental Protection Agency's Toxics Release Inventory (TRI) and tract-level demographic data from the 2000 U.S. census to determine whether environmental racial inequality existed in the Detroit metropolitan area in the year 2000. This study differs from prior environmental inequality research in two important ways. First, it offers a positive rationale for using hazard proximity indicators. Second, it uses a distance decay modeling technique to estimate hazard proximity. This technique weights each hazard's estimated negative effect by distance such that the estimated negative effect declines continuously as distance from the hazard increases, thus providing more accurate estimates of proximity-based environmental risk than can be obtained using other variable construction techniques currently found in the literature. Using this technique, I find that Detroit's black neighborhoods were disproportionately burdened by TRI facility activity in 2000 and that neighborhood racial composition had a strong independent effect on neighborhood proximity to TRI activity.

### Introduction

Over the past couple of decades, academic interest in environmental inequality has grown dramatically, resulting in the development of a large and expanding body of research that has attempted to determine whether minority and low income groups are disproportionately burdened by environmental hazards (Bowen 2002; Pastor, Sadd and Morello-Frosch 2002; Szasz and Meuser 1997). Although the methodological techniques researchers have used to make this determination have improved considerably over time, researchers still face several critical methodological challenges (Bowen 2002; Chakraborty and Armstrong 2001; Mennis 2002). One of the most important of these challenges is the problem of properly measuring residential proximity and exposure to environmental hazards and industrial pollution (Bowen 2002; Downey 2003; Liu 2001; Mohai and Saha 2006).

The problem facing researchers is two-fold. First, it is likely that the strength of an environmental hazard's negative effects declines continuously as distance from the hazard increases (Liu 2001). Thus, if researchers want to accurately measure environmental inequality, they must be able to model this continuous negative effect. Second, data limitations force most environmental inequality researchers to use demographic data that are tied to areal units of analysis such as census tracts and zip codes (Downey 2003). This is problematic because the boundaries used to create these areal units of analysis, although not designed arbitrarily, are arbitrary with respect to the distribution of environmental hazards. As a result, environmental hazards are often located near the physical boundaries of areal units of analysis, sometimes closer to neighboring units of analysis than to the far side of their host unit (Downey 2003).

This presents researchers with a real dilemma. Should they assume, as others have done, that an environmental hazard's negative effects are confined solely to and distributed evenly throughout its host unit of analysis (Downey 2003; Mohai and Saha 2006)? Or should they assume that environmental hazards negatively affect both host and non-host units? More importantly, because it is quite likely that environmental hazards' negative effects spread *unevenly* across both host and non-host units, how should they measure these uneven effects? And once measured how should they tie their measurements back to their demographic units of analysis?

This article provides some new answers to these questions by using a distance decay modeling technique borrowed from geographic information systems (GIS) analysts, industrial pollution data drawn from the Environmental Protection Agency's (EPA) Toxics Release Inventory (TRI), and tract-level demographic data drawn from the 2000 U.S. Census to determine whether environmental racial inequality existed in the Detroit metropolitan area in the year 2000.

I begin by describing the distance decay modeling technique and justifying its use. I then run a set of regression analyses that allows me to determine whether the distance decay estimates produced by the GIS modeling technique are positively associated with the percentages of Hispanics and non-Hispanic blacks in a census tract. Finally, I use these regression results to graph the associations that exist between the distance decay variables on the one hand and percent non-Hispanic black on the other (percent Hispanic is not positively associated with any of the distance decay variables). This allows me to draw more substantively meaningful conclusions about environmental racial inequality in Detroit than I otherwise could.

Before proceeding, I should note that the distance decay technique used in this article has two important limitations. First, it cannot overcome the aforementioned problem that environmental inequality researchers are generally forced to use areal units of analysis such as census tracts and zip codes. Thus, most researchers using this technique will have to aggregate their distance decay data to the areal-unit level in order to merge it with their demographic data. Second, because researchers do not know the actual rate at which environmental hazards' negative effects decline (their distance decay rate), the mathematical functions used to calculate distance decay are based on assumptions about the distance decay process rather than on precise knowledge of the process.

Although these are important limitations, they are not as serious as they first appear. This is because the first limitation results from a lack of address-specific, individual-level, demographic data, and not from any problem with the technique, and the second limitation results from the state of academic knowledge regarding distance decay. As a result, the first limitation can be overcome with better demographic data, and the second limitation will become less and less problematic as academic knowledge regarding the distance decay process improves.

## Literature Review

Environmental inequality researchers have studied the distribution of social groups around a variety of environmental hazards including hazardous waste sites, manufacturing facilities, superfund sites, chemical accidents and air pollutants (Bowen 2002; Derezinski, Lacy and Stretesky 2003; Morello-Frosch, Pastor and Sadd 2001; Szasz and Meuser 1997). Most studies support the hypothesis that lower income and minority neighborhoods are disproportionately burdened by environmental hazards. However, results have not been entirely consistent (Bowen 2002; Pastor, Sadd and Hipp 2001). For example, although most

researchers have found evidence of income- and/or poverty-based environmental inequality (Ash and Fetter 2004; Derezinski, Lacy and Stretesky 2003, Downey 2003; Morello-Frosch, Pastor and Sadd 2001), some have not (Anderton et al. 1994; Bowen et al. 1995; Brown, Ciambro and Hunter 1997).

Similarly, although many studies have found strong evidence of environmental racial inequality (Hamilton 1995; Krieg 1995; Mohai and Bryant 1992; Morello-Frosch, Pastor and Sadd 2001; Stretesky and Hogan 1998; Stretesky and Lynch 2002), some have found evidence of environmental racial inequality for some minority groups but not others (Brown, Ciambro and Hunter 1997; Pastor, Sadd and Morello-Frosch 2002; Sadd et al. 1999), and some have found only weak evidence of environmental racial inequality, inconsistent evidence, or none at all (Anderton et al. 1994; Atlas 2002; Bowen et al. 1995; Derezinski, Lacy and Stretesky 2003; Oakes, Anderton and Anderson 1996; Yandle and Burton 1996).

Studies have also varied according to whether they use a local (Bullard 1983; Mohai and Bryant 1992), regional, (Bowen et al. 1995; Downey 2003, 2005; Sadd et al. 1999), or national sample (Ash and Fetter 2004; Derezinski, Lacy and Stretesky 2003; Oakes, Anderton and Anderson 1996). Findings from local and regional studies suggest that patterns of environmental inequality vary from one locality and region to another (Bowen 2002), with studies of western metropolitan areas (Downey 2006; Brown, Ciambro and Hunter 1997; Pastor, Sadd and Hipp 2001; Pulido 2000) generally finding stronger evidence of environmental racial inequality than studies of rust belt cities or cities in the northeast and mid-Atlantic regions (Downey 2006; Bowen et al. 1995; Brown, Ciambro and Hunter 1997; Downey 2005).

## Proximity Indicators

Most environmental inequality researchers use residential proximity to environmental hazards, rather than exposure or risk, to measure environmental inequality (Bowen 2002; Sadd et al. 1999). Researchers use residential proximity data rather than exposure or risk data because exposure data are very difficult to obtain, and until recently air pollutant concentration data, which can be used to estimate certain kinds of health risks, have not been readily available (Ash and Fetter 2004; Morello-Frosch, Pastor and Sadd 2001).

The field's reliance on proximity data has been heavily criticized. For example, Bowen (2002) argues that lack of exposure and risk data seriously undermines the quality and usefulness of environmental inequality research because it prevents researchers from linking environmental hazards to specific public health outcomes in specific communities. This is problematic because it prevents researchers from determining whether environmental inequality exists and whether exposure to environmental pollutants has negative and inequitable public health outcomes.

Other scholars argue that lack of exposure and risk data, while problematic, is not nearly as serious as Bowen claims. Sadd et al. (1999:109) note, for example, that:

Several epidemiological studies have... demonstrated a significant relationship between residential proximity to urban toxic substances and/or air release facilities, and increased health risk and disease incidence, especially among pregnant women and infants.

Moreover, empirical evidence suggests that environmental hazards also negatively affect nearby property values, beliefs about local health risks, psychological stress, local employment opportunities, sense of community, and local economic activity (Downey and Van Willigen 2005; Liu 2001; Mohai 1995; Sadd et al. 1999), outcomes that are less likely to be affected by chemical exposure than they are to be affected by residential proximity to

environmentally hazardous facilities, the size and visibility of environmentally hazardous facilities, and perceptions of facility safety and neighborhood desirability. Thus, it is likely that in many cases proximity measures are more valid indicators than chemical exposure of environmental inequality.

This is not to say that exposure and risk data are unimportant or that the field would not benefit greatly from an increase in their use. It is simply to say that the field would also benefit greatly from improved proximity measures that take distance to hazardous facilities into account and, when possible, the size and visibility of these facilities and the social stigma that is attached to them.

## Measuring Proximity and Risk

Environmental inequality researchers have employed several strategies to measure residential proximity to environmental hazards and, when possible, to estimate environmental hazards' potential health risks. These strategies fall into three broad categories, the unit-hazard coincidence method, the buffer method and pollution plume modeling. The term *unit-hazard coincidence* was coined by Mohai and Saha (2006) to describe the most commonly used method of measuring residential proximity to environmental hazards. Researchers using this method locate environmental hazards on a map and (1) sum the number of hazards located in each of their study area analysis units, (2) sum the pounds of pollutants emitted in each of their study area analysis units, or (3) create a dummy variable that indicates whether or not an analysis unit contains a hazard. All individuals residing in an analysis unit containing an environmental hazard are considered to be living in equal proximity to that hazard, and only people living in that analysis unit are considered to be living in proximity to that hazard.

The unit-hazard coincidence method is problematic for several reasons, the most important of which is that it assumes that an environmental hazard's negative effects are confined solely to and distributed evenly throughout its host analysis unit. Figure 1 illustrates the problematic nature of these assumptions.

Figure 1 examines the distribution of Toxics Release Inventory (TRI) facilities in a subset of Detroit metropolitan area census tracts in the year 2000. TRI facilities are industrial facilities that manufacture, process or otherwise use specified toxic chemicals in specified quantities, and are required to report this use to the Environmental Protection Agency on an annual basis. (A more complete description of the TRI database can be found below.) Not only is it quite evident that TRI facilities are distributed unevenly within census tracts, it is also evident that TRI facilities are often located near the boundaries of multiple census tracts, in many cases closer to adjacent census tracts than to the far end of their host census tract. (Maps not shown here demonstrate that the same basic patterns hold for the region's hazardous waste facilities and National Priority List sites.)

Given the spatial distribution of these TRI facilities, it appears quite unlikely that their negative effects are confined solely to their host analysis units. It is also quite unlikely that the strength of their negative effects remains constant as the distance from each facility increases (Liu 2001; Pollock and Vittas 1995). Nevertheless, the unit-hazard coincidence method assumes both these things.<sup>1</sup>

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<sup>1</sup>The unit-hazard coincidence method assumes that an environmental hazard's negative effects remain constant until you reach the borders of its host analysis unit, at which point these effects abruptly drop to zero.

## The Buffer Method

Researchers using the buffer method to determine the geographic area and population affected by some set of environmental hazards locate these hazards on a map and then construct circular buffers around each hazard. These buffers, which are usually the same size for each facility,<sup>2</sup> are matched to areal units of analysis (such as census tracts) in a variety of ways. One approach is to define as an “affected analysis unit” any analysis unit that has at least 50 percent of its area encompassed by the buffer. Other approaches include defining an analysis unit as an “affected unit” if that unit’s centroid is encompassed by the buffer or if the buffer touches or in any way covers a portion of the analysis unit (Chakraborty and Armstrong 1997; Mohai and Saha 2006). Regardless of which approach is taken, they all consider any individual who lives in an affected analysis unit to be residentially proximate to all the hazards affecting that unit.

A fourth approach associated with the buffer method, the *areal apportionment method*, calculates the proportion of each analysis unit that is actually encompassed by a buffer and then assigns that proportion of the analysis unit’s population to the buffer (Mohai and Saha 2006). For example, if 22 percent of an analysis unit’s area is encompassed by a buffer, then 22 percent of that analysis unit’s population is considered to be affected, and 78 percent to be unaffected, by that buffer’s hazard.

The buffer method offers some important advantages over the unit-hazard coincidence method. Most importantly, the buffer method does not assume that environmental hazards’ negative effects are confined solely to host analysis units. In addition, the *areal apportionment method* does not assume that environmental hazards’ negative effects are distributed evenly within analysis units. Nevertheless, all buffer methods assume that the strength of a hazard’s negative effects remains constant within the circular buffer drawn around the hazard.

## Pollution Plume Modeling

Pollution plume modeling techniques, such as those used to derive the data employed in Ash and Fetter (2004) and Morello-Frosch, Pastor and Sadd (2001), do not make this problematic assumption. These studies use air pollutant concentration and toxicity data drawn from the Environmental Protection Agency’s (EPA) Cumulative Exposure Project (CEP: Morello-Frosch, Pastor and Sadd) and Risk-Screening Environmental Indicator’s project (RSEI: Ash and Fetter) to estimate health risk scores for each analysis unit in their respective datasets.

These data are unique in environmental inequality research, not only because they allow researchers to estimate the potential health risks associated with specific environmental hazards and specific analysis units, but also because the plume modeling techniques used to derive these data take into account factors such as wind speed, wind direction, air turbulence, smokestack height and the rate of chemical decay and deposition (Ash and Fetter 2004). As a result, these modeling techniques allow the concentration of air pollutants and, therefore, the estimated health risks associated with these air pollutants to (1) decline continuously as distance from the emitting source increases and (2) vary according to compass direction. In addition, because the pollution plumes used to derive the risk estimates can extend for miles in any direction (up to 44 miles in the RSEI model), this modeling technique allows hazards and emissions in one analysis unit to affect people living in other analysis units.

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<sup>2</sup>See Chakraborty and Armstrong (2001) for an interesting exception.

This is a clear improvement in many respects over the unit-hazard coincidence and buffer modeling approaches. Nevertheless, the plume modeling approach is not without its own set of limitations. First, the health risks associated with pollution exposure are not the only set of risks associated with environmental hazards. As noted above, environmental hazard presence can also negatively affect nearby property values, perceptions of local health risks, psychological stress, local employment opportunities, sense of community and local economic activity. For researchers interested in these potential negative impacts, plume modeling data are clearly inappropriate.

Second, creating plume modeling datasets for large geographic areas is a time consuming and expensive process. As a result, there are few large-scale plume model datasets and those that exist are limited to specific sets of hazards. Third, because of the difficulty inherent in estimating plume models for hundreds of thousands of releases across the entire United States, the plume modeling techniques used in Ash and Fetter (2004) and Morello-Frosch, Pastor and Sadd (2001) make several necessary but problematic assumptions. For example, each facility in the RSEI database is given a single smokestack height estimate. However, many industrial facilities have multiple smokestacks of varying height, smokestack height estimates are often based on the median smokestack height for an entire industry (based on the facility's three-digit SIC code), and in the RSEI model "stack height has the greatest impact on predicted concentrations of air pollutants." (Bouwes and Hassur 1999:ii) Moreover, the RSEI model assumes constant emissions rates and uses chemical decay estimates that are not necessarily accurate.

Thus, although plume modeling data represent a significant improvement in many respects over unit-hazard coincidence and buffer analysis data, such data are not as accurate as many researchers might think. More importantly, their use is limited to specific research questions (those having to do with specific public health risks) and specific hazards (those covered by the plume models).

Thus, in the next section of the article, I describe a GIS technique for creating hazard proximity indicators that can be used to model environmental hazards' non-exposure related negative effects. This technique takes into account the location and distribution of hazards within analysis units, allows the strength of an environmental hazard's negative effects to decline continuously as distance from the hazard increases, and permits hazards and emissions in one analysis unit to affect people living in other analysis units.

As noted earlier, this technique has some important limitations, and it is by no means a substitute for pollution plume modeling. Instead, it should be viewed as an important complement to the buffer analysis and plume modeling techniques already found in the literature.

## Distance Decay Modeling Using GIS

A GIS is a software package that unites spatial data, such as the *location* of factories and census tracts, with data about the features making up the spatial database, such as the number of people living in each census tract or the pounds of pollutants emitted from each factory. In a GIS, data are stored as map layers that can be precisely positioned on top of each other. There are two basic types of map layers in a GIS: vector map layers and raster map layers. A vector map uses points, lines and polygons to represent physical features such as cities, rivers and state boundaries. (Vector maps are what most people think of when they think of maps.) A raster map stores and displays spatially referenced numeric data in rectangular grids composed of square cells that are described in terms of resolution. For example, a 25-foot resolution raster map contains square grid cells with sides that are 25 feet long.



In order to create the *negative effects indicators* used in this article, industrial facilities from the 2000 Toxics Release Inventory were first located on a Detroit metropolitan area vector map, and then three, 105.6-foot resolution raster grids were calculated for each facility (105.6 feet is 1/50th of a mile). The first grid calculated the distance from the center of each cell in the metropolitan area to the center of the cell containing that grid's TRI facility. The second grid was a *weighting grid* that provided, for each metropolitan area grid cell, a weight ( $w$ , where  $0 \leq w \leq 1$ ) that indicated the relative strength of the facility's potential negative effect on that cell. This grid was calculated by inserting the distance values from the first grid into a distance decay function such as the following:

$$F(w)=1 - (5.0 * d * 10^{-6}) - (5.360422 * d^2 * 10^{-9}) \quad \text{for } 0 \leq d \leq 13,200 \quad (1a)$$

$$F(w)=0 \quad \text{for } d > 13,200, \quad (1b)$$

where  $d$  equals distance in feet from the TRI facility (this and other distance decay functions are employed in the analyses presented below).

The third grid, the *relative effects grid*, was calculated by multiplying each cell in the weights grid by the total pounds of air pollutants emitted by that grid's TRI facility in 2000. Ideally, this grid would be calculated by multiplying each cell in the weights grid by some measure of facility size or visibility in order to account for the fact that the strength of an environmental hazard's non-exposure related negative effects is likely a function, at least in part, of the size and visibility of the hazard (see earlier discussion). However, the TRI does not provide researchers with facility size or visibility data. Thus, I had to select a proxy for facility size from the variables included in the TRI dataset. I selected air emissions as my proxy because TRI facility air emissions are strongly correlated with facility size for a subset of facilities for which facility size data are available.

The *relative effects grids* for all the facilities in the database were then summed together to create a new grid in which each cell value represented the *summed relative effect* of all Detroit metropolitan area TRI facilities on that cell. For example, if there had been five facilities in the study area, and the *relative effect* of these facilities on grid cell A had been 0, 300, 10, 500 and 0 respectively, then their *summed relative effect* on grid cell A would have equaled  $0 + 300 + 10 + 500 + 0$ , or 810.

Finally, the cell values in the *summed relative effects* grid were aggregated to the census tract level by summing together the cell values in each census tract and then dividing each census tract total by the number of cells in that tract. The resulting indicator, the *mean relative effect* indicator, provides an estimate of the relative effect of all study area facilities on each study area census tract.<sup>3</sup>

## Functional Form

One of the strengths of the variable construction technique described in the previous section is that it allows researchers to vary the distance decay functions used to calculate the relative effects grids in any manner they want. Unfortunately, however, the environmental inequality

<sup>3</sup>It should be kept in mind that these *relative effects averages* do not represent average air pollutant concentration levels, the total pounds of air pollutants emitted in the average analysis unit grid cell, or some absolute measure of hazard impact on each analysis unit. Instead they are estimates of the *relative*, non-exposure-related impact of all study area facilities on each study area analysis unit. Thus a score of 1,000 indicates twice the estimated impact of a score of 500, but has no absolute meaning of its own (RSEI risk scores are also interpreted relative to one another and not in absolute terms).

literature provides researchers with little guidance on how to determine, for any potential negative effect, the proper functional form for the distance decay equations. As a result, there is no theoretical or empirical reason for favoring one functional form over another.

Given this problem, this article provides results for six distance decay indicators. Figure 2 presents graphs of the weighting functions used to calculate two of these indicators. Each graph in figure 2 graphs the line created by plotting distance (in feet) from the hazard against the weight assigned for that distance by the graph's particular decay function. Graph A plots a 1.5 mile *curvilinear* distance decay function and graph B plots a 1.5 mile *inverse curvilinear* distance decay function. The curvilinear function assumes that an environmental hazard's negative effects decline relatively slowly at first and more quickly as distance increases. The inverse curvilinear function assumes that an environmental hazard's negative effects decline relatively rapidly at first and more slowly as distance increases. In each of these graphs, the weight reaches zero at 1.5 miles and remains at zero thereafter. However, results are also reported below for curvilinear and inverse curvilinear functions that reach zero at .5 miles and 2.5 miles.

The .5, 1.5 and 2.5 mile cutoff points were chosen because studies that examine the impact of hazardous waste sites on property values have generally found that property values are affected at distances ranging from .25 miles in some studies to more than 2 miles in others (Mohai 1995; Liu 2001). In addition, because little is known about the spatial extent of other potential negative effects, it makes more sense to examine how results vary across multiple cutoff points than it does to select a single cutoff point for examination.

Finally, I ran regression models using other linear and non-linear distance decay indicators. Results for these models are not reported in this article because they do not differ appreciably from the regression results reported below.

## Study Area

The Detroit metropolitan area is defined here as the six counties that the U.S. Census Bureau designates as comprising the 2000 Detroit Primary Metropolitan Statistical Area (these counties are Lapeer, Macomb, Monroe, Oakland, Saint Clair and Wayne counties). I selected Detroit for this study because it represents one of this nation's most important rust belt cities and because TRI emissions and waste transfers in Wayne County, Detroit's host county, are among the worst in the nation. (Wayne County consistently ranks among the 10 most polluted counties in the United States.)

In contrast to studies of western metropolitan areas (Downey 2006; Brown, Ciambrone and Hunter 1997; Pastor, Sadd and Hipp 2001; Pulido 2000), studies of rust belt cities have generally found relatively weak evidence of environmental racial inequality (Bowen et al. 1995; Brown, Ciambrone and Hunter 1997; Downey 2005). In Detroit, this may be explained by the fact that unlike industry, blacks have been confined primarily to the urban core. Thus, research has shown that by 1990, industrial facilities in Detroit's urban core were surrounded almost entirely by black neighborhoods, while industrial facilities in Detroit's suburbs were surrounded almost entirely by white neighborhoods, resulting in relatively low levels of environmental racial inequality at that time (Downey 2003, 2005; Krieg 1995 found similar patterns in the Boston metropolitan area in 1990).

Of course, environmental inequality levels in Detroit may have changed between 1990 and 2000. For example, demographic changes may have placed a greater share of Detroit's black residents in suburban industrial neighborhoods than was previously the case, increasing environmental racial inequality levels in the region. Conversely, industrial facilities may have left Detroit's urban core in numbers large enough to weaken environmental racial



inequality in the region, as appears to have happened in the period between 1970 and 1990 (Downey 2005). Finally, this study may find different levels of environmental inequality in Detroit than have previous studies simply because this study uses different hazard indicators and a different study area definition than have previous studies.

## Environmental Hazard Data

Environmental hazard data were obtained from the Environmental Protection Agency's 2000 Toxics Release Inventory. The TRI records the number of pounds of specified toxic chemicals released into the environment each year by industrial facilities that fall into one of seven industrial categories (manufacturing, metal mining, coal mining, electric generating facilities that combust coal or oil, chemical wholesale distributors, petroleum terminals and bulk storage), employ the equivalent of 10 or more full-time workers, and manufacture, process or otherwise use the specified chemicals in specified quantities. In 2000, the specified quantities were 25,000 pounds for facilities that manufactured or processed TRI chemicals and 10,000 pounds for facilities that otherwise used TRI chemicals (Rtknet 2004)<sup>4</sup>.

The TRI reports toxic chemical releases to various media, including air, land, water and underground injection. It also provides data on off-site waste transfers and waste generated on-site. *Total air releases*, which are used to calculate the relative effects grids discussed above, are the sum of each facility's stack and fugitive air emissions. Stack air emissions are emissions that exit the TRI facility through a confined air stream such as a pipe or a stack. Fugitive air emissions, such as leaks and evaporation, are air emissions that are not released through a confined air stream (Rtknet 2004).

As noted above, *total air releases* is used as a proxy for facility size because the TRI provides no direct measure of facility size and such measures are unavailable from other sources. Dun and Bradstreet, for example, provide square footage data for many industrial facilities, but for only 49.5 percent of the facilities included in the database used in this article. However, when total air releases is correlated with the square footage of TRI facilities for which square footage data is available, the correlation equals .71 ( $p < .0001$ ), providing evidence that total air releases is a good proxy for facility size. (None of the other TRI variables are as strongly correlated with the square footage variable.)

Finally, TRI facilities were located on a map using latitude and longitude coordinates provided by the EPA. Because the estimated accuracy of these coordinates varies from less than 100 meters to 11,000 meters, only those facilities with coordinate accuracy estimates *less than or equal to* 150 meters were included in the dataset. In other words, only facilities estimated to be within 150 meters or less of the latitude and longitude coordinates provided by the EPA are included in the dataset.<sup>5</sup> The resulting dataset includes approximately 85.8 percent of the original observations.<sup>6</sup>

## Demographic Data

Tract-level demographic data were obtained from the 2000 U.S. Census. Demographic variables were selected based on their inclusion in prior studies that have attempted to determine the relative importance of race and income in predicting environmental hazard

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<sup>4</sup>See Sadd et al. (1999) and Downey (2006) for a detailed discussion of the advantages and limitations of TRI data.

<sup>5</sup>Details on the process that the EPA uses to determine TRI facility latitude and longitude coordinates and to estimate the accuracy of these coordinates can be found at the following website: [http://www.epa.gov/opptintr/rsei/docs/tech\\_app\\_d.pdf](http://www.epa.gov/opptintr/rsei/docs/tech_app_d.pdf).

<sup>6</sup>Restricting the dataset to facilities with coordinate accuracy estimates of less than 150 meters would have resulted in a dataset with only 1.5 percent of the original observations.

presence (Anderton et al. 1994; Oakes, Anderson and Anderton 1996; Pastor, Sadd and Hipp 2001; Sadd et al. 1999). Demographic variables include percent Hispanic, percent non-Hispanic black, median household income, the percentage of employed tract residents who are engaged in manufacturing occupations (percent employed in manufacturing), the number of people per square mile (population density), the percentage of tract residents living in poverty (percent poverty), the median property value of owner occupied housing (median property value), the median age of owner occupied housing (median housing unit age), the percentage of residents 25 years old or older who have completed 12 or more years of schooling but who do not have a four-year college degree (percent high school or some college), the percentage of housing units that are vacant (percent vacant housing units), and the distance from each tract's average grid cell to the nearest railroad line (average railroad distance).

*Median household income, percent living in poverty and median property value* were selected because several scholars have argued that the reason minorities are overrepresented in environmentally hazardous neighborhoods is that housing costs are relatively low in such neighborhoods, making them attractive to lower income people who, in turn, are disproportionately non-white (Hamilton 1995; Mohai and Bryant 1992; Oakes, Anderton and Anderson 1996).

*Percent employed in manufacturing* is included because some researchers have hypothesized that industrial facilities and industrial workers tend to locate near each other (Anderton et al. 1994a). *Population density* is included because manufacturing facilities are often sited in areas with plenty of open space (Downey 2005) and because some researchers have argued that local officials work to reduce pollution levels in areas with high population densities (Ash and Fetter 2004; Sadd et al. 1999). *Average railroad distance* is included because Detroit's industrial neighborhoods tend to be located near the region's railroad lines (Downey 2005). *Median housing unit age* and *percent vacant housing units* are included because I hypothesize that industrial facilities are overrepresented in older, somewhat run-down neighborhoods. Finally, the education variable is included because neighborhood education levels have been significantly associated with environmental risk levels in prior environmental inequality research (Ash and Fetter 2004).<sup>7</sup>

## Results

In order to determine whether environmental inequality existed in the Detroit metropolitan area in 2000, Table 1 correlates percent Hispanic, percent non-Hispanic black and median household income with the distance decay indicators discussed above. Table 1 shows that percent Hispanic is insignificantly associated with all six distance decay indicators, that percent non-Hispanic black is positively and significantly associated with the 1.5 and 2.5 mile distance decay indicators, but not with the .5 mile distance decay indicators, and that median household income is negatively and significantly associated with all six distance decay indicators. In addition, Table 1 shows that none of the significant correlation coefficients are very large. Thus, it appears that black environmental inequality and income-based environmental inequality both existed in the Detroit metropolitan area in 2000, but they were both relatively weak at that time.

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<sup>7</sup>I originally included two education variables in the analysis, the percentage of tract residents 25 years old and older with a college degree or higher and the percentage of tract residents 25 years old and older with less than a high school degree. Because these variables were both positively associated with all the dependent variables, I re-ran the regression models using the education variable that is defined in the main text. This variable is consistently and negatively associated with the dependent variables.

In order to determine whether percent non-Hispanic black is still a statistically significant predictor of environmental hazard presence after controlling for other important predictors of environmental hazard presence, I regress each of the 1.5 and 2.5 mile distance decay indicators on percent non-Hispanic black (tables 2–3), controlling for percent Hispanic, median household income and the other control variables discussed above. (Results are not reported for the .5 mile distance decay indicators because neither of them is significantly correlated or associated with percent Hispanic or percent non-Hispanic black.)

Although it is possible that percent Hispanic, percent non-Hispanic black and median household income are linearly related to the dependent variable, this is not necessarily the case. For example, it may be that after neighborhood incomes reach a certain point, further income increases can only buy limited environmental improvements because environmental conditions are already at or near perfect. Similarly, if researchers are correct in arguing that environmental racial inequality exists because minorities have limited residential choice (Downey 2005), then any positive association that exists between percent minority and environmental hazard presence may level off as the percentage of minorities in a neighborhood increases beyond a certain point. In other words, just as increased residential choice may no longer buy improved environmental conditions beyond a certain point, it may also be the case that decreased residential choice no longer results in worse environmental conditions beyond a certain point.

Thus, most of the regression models presented below include logged transformations of percent Hispanic, percent non-Hispanic black and median household income. The one exception is found in Table 3, where percent Hispanic is employed rather than percent Hispanic logged because the latter variable is insignificantly associated with either of the dependent variables in either the full or reduced regression models.

Table 2 regresses each of the 2.5 mile distance decay indicators on the transformed race and income variables, controlling for the demographic and housing variables discussed above. Models 1–3 present results for the curvilinear indicator and models 4–6 for the inverse curvilinear indicator. The independent variables are stepped into the equation in three stages: models 1 and 4 only include percent non-Hispanic black logged; models 2 and 5 step in percent Hispanic logged and median household income logged; and models 3 and 6 step in the remaining control variables. Percent Hispanic logged and median household income logged are stepped into the equation in the same model because inserting percent Hispanic logged into the equation separately has virtually no effect on the coefficients found in models 1 and 4. Thus, models 2 and 5 allow me to determine whether inserting median household income logged into the equation weakens any of the positive associations that exist between percent non-Hispanic black logged and the 2.5 mile distance decay indicators. Finally, because the residuals from ordinary least squares (OLS) estimates were spatially correlated with one another, these models, and those found in table 3, control for spatial autocorrelation.

Table 2 shows that percent non-Hispanic black logged is significantly and positively associated with the 2.5 mile curvilinear indicator in model 1 and the 2.5 mile inverse curvilinear indicator in model 4. The associations between percent non-Hispanic black logged and the two dependent variables are weakened when median household income logged is inserted into the equation in models 2 and 5 and when the remaining control variables are inserted into the equation in models 3 and 6. Nevertheless, percent non-Hispanic black logged is still significantly associated with the dependent variable in both full models. Thus, as percent non-Hispanic black increases, the 2.5 mile curvilinear and inverse curvilinear indicators both increase, but at a declining rate.

Table 3, which presents results for the 1.5 mile distance decay indicators, shows that percent non-Hispanic black logged is significantly and positively associated with the 1.5 mile curvilinear indicator in model 1 and the 1.5 mile inverse curvilinear indicator in model 4. The associations between percent non-Hispanic black logged and the two distance decay indicators are weakened when median household income logged is inserted into the equation in models 2 and 5 and when the remaining control variables are inserted into the equation in models 3 and 6. Nevertheless, percent non-Hispanic black logged is still significantly associated with the dependent variable in model 3 and marginally associated with the dependent variable in model 6 ( $p = .0585$ ). Thus, as percent non-Hispanic black increases, the 1.5 mile curvilinear and inverse curvilinear indicators both increase, but at a declining rate.

As previously stated, regression results are not reported in table form for the .5 mile distance decay indicators because neither of these indicators is significantly associated or correlated with percent Hispanic or percent non-Hispanic black. Nevertheless, it should be noted that in the .5 mile regression analyses, median household income logged is significantly and negatively associated with both distance decay indicators in both full regression models.

Finally, unreported regression analyses were also run using two unit-hazard coincidence indicators as dependent variables: the total number of TRI facilities in each census tract in 2000 and the total pounds of TRI air pollutants emitted in each census tract in 2000. In these analyses, median household income logged is significantly and negatively associated with both hazard indicators. However, neither hazard indicator is significantly associated with percent Hispanic, percent non-Hispanic black or either of these variables' logged terms.

## Discussion

The results presented in the previous section demonstrate that Detroit's black neighborhoods were disproportionately burdened by TRI facility activity in 2000 and that the associations between percent non-Hispanic black logged and the 1.5 and 2.5 mile hazard indicators remained statistically or marginally significant even after controlling for a set of theoretically relevant neighborhood characteristics. Thus, it appears that neighborhood racial status played an important role in shaping environmental inequality in the Detroit metropolitan area in 2000.

One could argue that the relatively weak correlation coefficients found in Table 1 and the unreported regression results for the .5 mile hazard indicators show that neighborhood racial status played little or no role in shaping environmental inequality in the Detroit metropolitan area. However, as Mohai (1995) points out, it is unlikely that environmental hazards' negative effects are ever confined to an area with a radius as small as .5 miles. In addition, the findings in Table 1 do not negate the fact that percent non-Hispanic black logged is significantly or marginally associated with the 1.5 and 2.5 mile hazard indicators in all four full regression models.

But perhaps most importantly, when the relationships between percent non-Hispanic black and the 1.5 and 2.5 mile hazard indicators are graphed out, as they are in Figure 3, neighborhood racial composition appears to be a *substantively* important predictor of a neighborhood's mean relative effect levels.

Graphs A and B in Figure 3 were created using the results from the full models in tables 2 and 3, holding the values of the other statistically significant or marginally significant independent variables constant at their respective means and the values of the statistically insignificant independent variables constant at zero. The values of the dependent variables (divided by 1,000) are listed on the y-axes and are different in each graph.

Graphs A and B demonstrate that even after controlling for a host of other factors, predominantly black neighborhoods in the Detroit metropolitan area had much higher mean relative effect values than did other neighborhoods. For example, graph A shows that as percent non-Hispanic black increases from 0 to 100, (1) the 2.5 mile curvilinear indicator increases from 74,316 to 131,464, a 57,148 point increase, and (2) the 2.5 mile inverse curvilinear indicator increases from 24,481 to 38,111, a 13,630 point increase. Thus, if we consider the curvilinear and inverse curvilinear functions to represent the endpoints of a reasonable “distance decay function continuum,” Detroit metropolitan area neighborhoods that were 100 percent non-Hispanic black had mean relative effect values between 13,630 and 57,148 points higher than did Detroit metropolitan area neighborhoods that were 0 percent non-Hispanic black.<sup>8</sup>

Moreover, graph A shows that although much of this increase occurs in neighborhoods that are between 0 and 10 percent non-Hispanic black, much of it does not. For example, the inverse curvilinear indicator, which equals 24,481 at 0 percent non-Hispanic black and 31,296 at 10 percent non-Hispanic black, increases to 36,059 at 50 percent non-Hispanic black and 37,799 at 90 percent non-Hispanic black. Similarly, the curvilinear indicator, which equals 74,316 at 0 percent non-Hispanic black and 102,890 at 10 percent non-Hispanic black, increases to 122,863 at 50 percent non-Hispanic black and 130,157 at 90 percent non-Hispanic black.

The substantive importance of neighborhood racial composition is further confirmed by comparing graphs A and B to graphs C and D. Graphs C and D, which are identical to each other, graph out the empirical distribution functions of the metropolitan area’s black and white populations when metropolitan area census tracts are ranked (from 0 to 100) according to the percentage of non-Hispanic blacks in each tract. These graphs show, for example, that 81.7 percent of metropolitan area whites, but only 3.7 percent of metropolitan area blacks, live in census tracts that are 5 percent or less non-Hispanic black. They also show that 89.9 percent of metropolitan area whites, but only 5.9 percent of metropolitan area blacks, live in census tracts that are 10 percent or less non-Hispanic black.

Thus, the graphs in Figure 3 demonstrate that the independent effect of percent non-Hispanic black on the 1.5 and 2.5 mile hazard indicators is quite substantial. As a result, we can safely conclude that environmental racial inequality was a serious social problem in the Detroit metropolitan area in 2000.

An important question still remains however. How exactly does a 13,630 or 57,148 point increase in a tract’s mean relative effect level affect tract residents? Are such increases large enough to affect nearby property values, beliefs about local health risks, local economic activity, psychological stress or sense of community? Are they large enough to produce some of these negative effects but not others?

In order to answer these questions, researchers will need to carefully investigate the relationship between residential proximity to environmental hazards and these hypothesized negative effects. As noted above, some researchers have already begun to do so (Downey and Van Willigen 2005; Liu 2001; Mohai 1995). However, what is needed is research that

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<sup>8</sup>Comparing graphs A and B, we see that the predicted values of the dependent variables vary more when we hold these variables’ cutoff distance constant and vary their functional form than when we hold their functional form constant and vary their cutoff distance. In other words, in these models it appears that functional form has a stronger influence on regression results than does cutoff distance. This is a striking and somewhat surprising finding, especially when we consider that varying the cutoff distance from .5 to 1.5 miles has a substantively significant effect on correlation and regression results. Explaining why functional form matters more than cutoff distance in the 1.5 and 2.5 mile regression models is beyond the scope of this article, but it clearly merits further investigation.

links these hypothesized negative effects to specific distance decay indicators and specific *mean relative effect* levels.

For example, researchers could merge distance decay indicators such as those employed in this article with survey and census data to examine the effect that environmental hazards have on neighborhood disorder and depression. Similarly, researchers could merge distance decay indicators with economic data to examine the impact that environmental hazards have on nearby property values and local economic activity.

Researchers could then use their findings to link specific distance decay indicators to specific negative effects, allowing them to determine, for each of these negative effects, (1) how much relative effect values have to increase in order to negatively affect individuals and neighborhoods or (2) whether there is some threshold value at which individuals and neighborhoods are negatively affected. These results could then be combined with the kind of results reported in this article to determine whether minority and low income neighborhoods are disproportionately burdened by environmental hazards' proximity-related negative effects.

Although conducting such analyses is clearly beyond the scope of this article, the true substantive significance of the findings reported here, and of environmental inequality research in general, cannot be understood until researchers are able to link inequitable proximity to specific proximity-related negative outcomes. (Bowen 2002 makes the same point about environmental hazards' exposure-related risks.) Because distance decay indicators are highly flexible and provide researchers with more accurate estimates of environmental hazards' non-exposure related risks than can be obtained using other hazard proximity indicators, they are ideally suited for establishing such a link.

## Conclusion

As with any study, caution must be taken in interpreting the findings reported here. For example, because the data for this study are drawn from a single metropolitan area, the results cannot be generalized to other metropolitan areas or to the United States as a whole. In addition, because this study uses aggregated census tract data, the cell values in the summed relative effects grids had to be aggregated to the census tract level, resulting in a significant loss of information and minimizing to some unknown degree the advantages of using grid cell data (*the aggregated data problem*). Finally, because the literature provides little guidance on properly estimating distance decay rates, the hazard indicators employed in this article were calculated using a range of distance decay functions and cutoff distances rather than a set of decay functions and cutoff distances tailored to specific negative outcomes. As a result, the hazard indicators employed in this article do not provide as precise a set of proximity-based risk estimates as they otherwise would.

These caveats notwithstanding, this study makes several contributions to the environmental inequality literature. First, it introduces a distance decay modeling technique that more accurately estimates proximity-based environmental risk than do other modeling techniques currently found in the literature. It more accurately estimates proximity-based risk because it does not assume that an environmental hazard's negative effects are confined solely to its host unit of analysis, that the strength of these negative effects remains constant as distance from the hazard increases, or that these negative effects are distributed evenly within analysis units; and unlike plume modeling techniques, this technique can be used to estimate non-exposure related risks. The technique is also highly flexible, capable of incorporating *any* distance decay function that researchers deem appropriate.



Moreover, the technique's shortcomings are not as serious as they first appear. As noted in the introduction, the aggregated data problem results from a lack of address-specific, individual-level, demographic data, not from any problem with the technique. The solution, therefore, involves either gathering or obtaining appropriate demographic data or developing techniques for apportioning aggregated demographic data across grid cells so that it can be matched to the grid cells used in the summed relative effects grids. Mennis (2002) provides one interesting approach for apportioning aggregated demographic data across grid cells and researchers should consider other approaches as well.

The lack of academic knowledge regarding distance decay rates is likewise not a limitation inherent to the technique. Rather, it results from the fact that environmental inequality is a relatively new field of research and thus, researchers have not had the time to solve all the important methodological issues facing them. As the field develops and researchers gain a better understanding of the relationship between proximity and risk, the distance decay functions researchers use will become more and more precise.

Second, this article provides environmental inequality researchers with a solid rationale for using hazard proximity indicators. Prior to this, many researchers have argued that the only reason to use proximity data is that proximity data are a reasonable proxy for exposure data, which are generally unavailable to researchers (Sadd et al. 1999). This article argues instead that proximity indicators are just as important as exposure indicators because environmental hazards have proximity-related negative effects that are poorly captured by exposure data.

Third, this article demonstrates that environmental racial inequality can be a serious social problem even when correlations between minority presence and environmental hazard presence are relatively weak, suggesting that researchers need to be attentive not only to the statistical significance of their findings but to their substantive significance as well.

Finally, the finding that percent non-Hispanic black logged is significantly associated with the 1.5 and 2.5 mile hazard indicators, but not with the .5 mile or unit-hazard coincidence indicators, has two important implications. First, it suggests that although neighborhoods between approximately .5 and 2.5 miles of Detroit's TRI facilities are disproportionately black, neighborhoods that actually house TRI facilities or are immediately adjacent to TRI facilities are not. This is consistent with Anderton et al.'s (1994) findings regarding hazardous waste sites, suggesting that this may be an important residential pattern for researchers to explain.

Second, this finding suggests that previous studies that have used unit-hazard coincidence indicators may have underestimated the significance of environmental racial inequality. This is important because environmental inequality researchers have used unit-hazard coincidence indicators more often than they have used any other type of environmental hazard indicator (Mohai and Saha 2006). Thus, this study suggests that a large body of environmental inequality research may underestimate the significance of race in shaping environmentally inequitable outcomes.

## Acknowledgments

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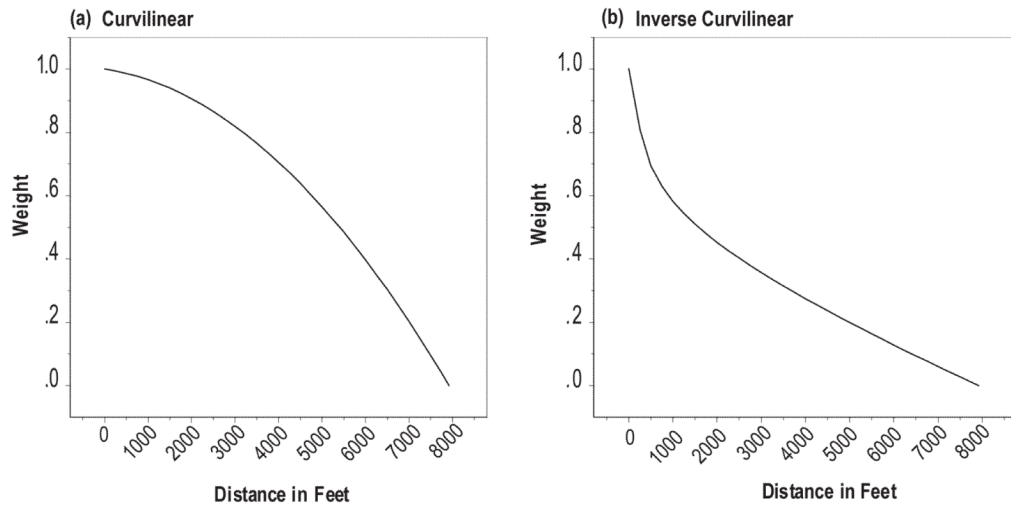
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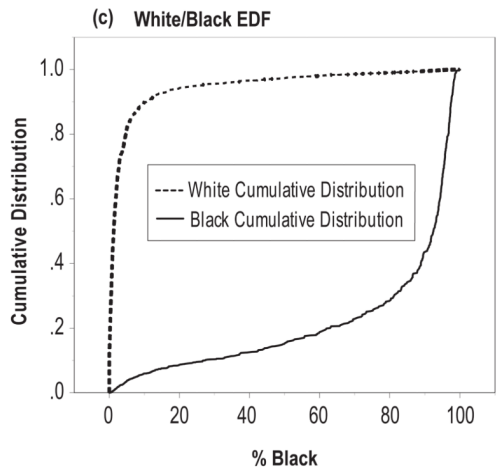
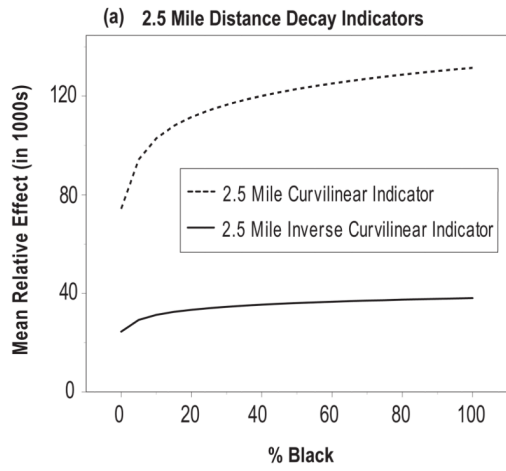
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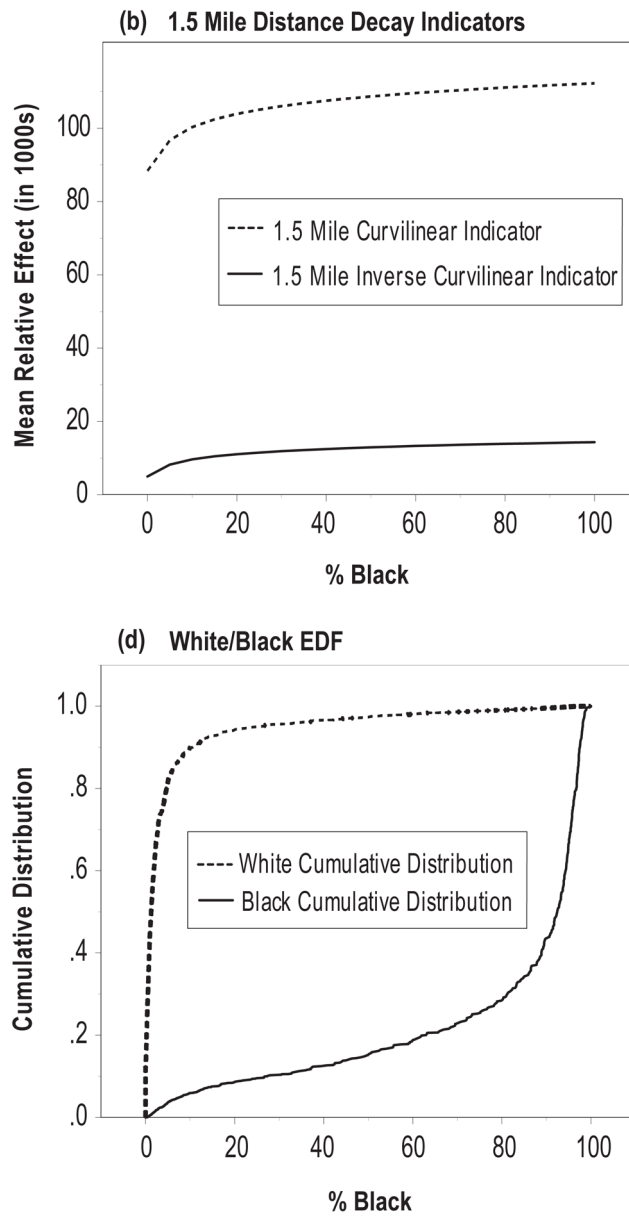
**Figure 1.**  
Detroit Metropolitan Area Census Tracts and TRI Facility Location, 2000



**Figure 2.**  
Distance Decay Functional Form Graphs







**Figure 3.**  
Regression Curves for 1.5 and 2.5 Mile Distance Decay Indicators

**Table 1**

Pearson's Correlation Coefficients for the Distance Decay Indicators and Demographic Variables

	Percent Hispanic		
	2.5 Mile	1.5 Mile	.5 Mile
Curvilinear	-.0198	-.0033	.0169
Inverse Curve	-.0214	-.0001	.0189
	Percent Non-Hispanic Black		
	2.5 Mile	1.5 Mile	.5 Mile
Curvilinear	.2031***	.1057***	.0436
Inverse Curve	.1787***	.0981***	.0403
	Median Household Income		
	2.5 Mile	1.5 Mile	.5 Mile
Curvilinear	-.2364***	-.1541***	-.0902**
Inverse Curve	-.2147***	-.1467***	-.0894**

\*  
p < .05\*\*  
p < .01\*\*\*  
p < .001

Table 2

Regression of 2.5 Mile Distance Decay Indicators on Demographic Variables

	Model 1 (Curve)	Model 2 (Curve)	Model 3 (Curve)	Model 4 (Inverse Curve)	Model 5 (Inverse Curve)	Model 6 (Inverse Curve)
Intercept	44576.46***	285769.39***	239722.80*	8713.74**	82247.46***	86344.29**
% Non-Hispanic Black Logged	23393.41***	14850.48***	12409.61**	5761.93***	3147.75**	2959.75**
Percent Hispanic Logged		-8746.59	-16167.36**		-2310.83	-3849.63*
Median Household Income Logged		-56969.93***	-31818.63 <sup>†</sup>		-17459.75***	-12997.56*
% Poverty			-497.69			-493.79
% Poverty Squared			-1.67			5.41
Population Density			-.77			-.61
% Employed in Manufacturing			1701.49*			402.10 <sup>†</sup>
Median Property Value			-.08			-.03
% High School or Some College			-1058.48*			-336.05*
% Vacant Housing Units			1611.64			471.37 <sup>†</sup>
Median Housing Unit Age			1133.88**			274.33*
Average Railroad Distance			-18624.42***			-4177.28***
Rho	.1374*	.1374*	.1374*	.1373*	.1373*	.1373*
Log-Likelihood	-1863	-1862	-1859	-1707	-1705	-1703
Number of Observations	1249	1249	1249	1249	1249	1249

<sup>†</sup>

p &lt; .10

\* p &lt; .05

\*\* p &lt; .01

\*\*\* p &lt; .001

Table 3

Regression of 1.5 Mile Distance Decay Indicators on Demographic Variables

	Model 1 (Curve)	Model 2 (Curve)	Model 3 (Curve)	Model 4 (Inverse Curve)	Model 5 (Inverse Curve)	Model 6 (Inverse Curve)
Intercept	12268.81*	142540.09***	157523.45***	4347.62†	57965.44***	68634.00**
% Non-Hispanic Black Logged	10467.44***	5778.84*	5177.72*	4045.33***	2111.43*	2033.10†
Percent Hispanic		-490.75	-930.57*		-171.39	-318.61†
Median Household Income Logged		-31545.05***	-18327.14		-13007.24***	-8909.44†
% Poverty			-1027.19			-459.85
% Poverty Squared			15.71			6.42
Population Density			-1.59			-.75†
% Employed in Manufacturing			1028.64*			356.25†
Median Property Value			-.10*			-.04*
% High School or Some College			-901.75**			-333.70**
% Vacant Housing Units			847.00			328.58
Median Housing Unit Age			342.01			122.50
Average Railroad Distance			-7591.60**			-3024.36**
Rho	.1369**	.1369**	.1368**	.1365**	.1365**	.1365**
Log-Likelihood	-1806	-1805	-1803	-1699	-1698	-1696
Number of Observations	1249	1249	1249	1249	1249	1249

† p&lt;.10

\* p&lt;.05

\*\* p&lt;.01

\*\*\* p&lt;.001