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Empowerment Through Risk-Related Information: EPA's Risk Screening Environmental Indicators Project

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Program on Development, Peacebuilding, and the Environment
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Introduction

Public access to information can drive change more effectively than regulations alone. Some regulatory agencies are now taking such an approach to advance their objectives. Right-to-know legislation, such as the Emergency Planning and Community Right-to-Know Act of 1986 (EPCRA), provides the basis for many of the U. S. Environmental Protection Agency's (EPA) information disclosure initiatives. By requiring that the public be informed about releases of toxic chemicals in their communities, EPCRA—through its Toxics Release Inventory (TRI) in particular—can help to empower community residents, heighten industry accountability to the citizenry, and support efforts to ensure environmental justice.

The availability of basic data is necessary, but not necessarily sufficient, to accomplish environmental justice objectives. The challenge is to verify the existence of *disparate impacts* (e.g., disparities correlated with race and income) and to identify where they occur, who is impacted, and who is responsible. To answer correctly such questions, it is necessary to translate data into accessible, meaningful information. The Risk-Screening Environmental Indicators (RSEI), a unique and advanced computer tool developed by EPA's Office of Pollution Prevention and Toxics, has the capability to translate toxic chemical release data into more meaningful risk-related information required by researchers and activists to analyze disparate impacts by race and income and to focus properly risk-reduction efforts in communities.

The Toxics Release Inventory

A community's right-to-know

In the early morning of December 3, 1984, methyl isocyanate, a highly toxic chemical used in production of an insecticide, escaped from the Union Carbide facility located in the midst of Bhopal, India, a heavily populated area of 800,000 people. This accidental release resulted in the immediate deaths of 2,000 people and injured approximately 300,000 others. It is estimated that an additional 8,000 may have died later as a result of their exposure. City health officials had not been informed of the toxicity of the chemicals used at the Union Carbide factory. There were no emergency plans or procedures in place, and no local knowledge of how to deal with the poisonous cloud.

Since Union Carbide was an American-held company, Congress and the public were confronted with the possibility that such an incident also could occur at a similar facility in the U.S. In fact, in 1985, Union Carbide accidentally released this same chemical in Institute, West Virginia, injuring 140 people. These events led to the enactment in the following year of EPCRA. Provisions of this Act promote emergency planning to minimize the effects of an accident such as that which occurred at Bhopal, and mandate the provision of public information on releases of toxic chemicals in all U.S. communities.

Section 313 of EPCRA established the TRI. This regulation requires manufacturing (Standard Industrial Classification (SIC) codes 20 through 39) and several other industry sectors and facilities in specified and federal facilities in any SIC code, to report on releases of chemicals into the air, water, or land if they meet certain employee and chemical thresholds.[1] Specifically, a facility must report the pounds of its releases and transfers of any of the 604 chemicals and chemical categories that are currently on the TRI list if it (1) has 10 or more full-time employees, and (2) “manufactures” or “processes” more than 25,000 pounds, or “otherwise uses” more than 10,000 pounds, of any listed chemical during the reporting year.[2] In 1997, 21,490 facilities reported TRI releases; more than 43,000 facilities have reported TRI data since 1987.

The TRI offers the public direct access to detailed information about releases and management of toxic chemicals in their specific communities. EPA compiles the information submitted by facilities nation-wide into an on-line, publicly-accessible database that reports releases of these toxic chemicals. Each year, EPA publishes a TRI Public Data Release with various views of the data collected for that reporting year; it also provides this data on the EPA website.

How are TRI data used?

Broad spectrums of private and public groups use TRI data. Concerned citizens use TRI to raise and answer questions about chemicals in their local communities, and the possible risks to public health and the environment. TRI serves as a public “report card” for the industrial community, creating public relations incentives for waste reduction, and providing local residents and public interest groups with credible grounds on which to pressure company executives and public officials for changes in industrial practice and public policy. Between 1989 and 1994 alone, public interest and community groups published over 200 reports using the TRI data (Orum 1994). There is considerable anecdotal evidence that information made available through right-to-know laws has contributed significantly to community organizing efforts to change facility emission behavior (see, for example, Lynn *et al.* 1992; MacLean 1993; Settina and Orum 1990, 1991; US EPA 1998.) Industry leaders have acknowledged the effect on their behavior: in a survey of about 200 corporate counsels, over half indicated that “pressure from community activists has affected [their] company’s conduct – sometimes forcing a reduction in pollution” (Lavelle 1993).

State and local agencies rely on TRI to establish emergency planning procedures, to formulate and pass critical legislation, and to enable toxic waste monitoring in communities. Many states have passed right-to-know legislation that expands the data collected under TRI and, in some cases, mandates reductions in emissions. In Louisiana in 1989, the TRI data prompted the passage of a new air toxics law requiring a 50 percent reduction of emissions by 1994. Several states have established programs at universities, such as the Toxics Use Reduction Institute at the University of Massachusetts – Lowell.

Most state environmental protection departments provide technical assistance to aid businesses in reducing toxic releases and other forms of pollution.

Federal agencies use TRI to prepare and implement environmental legislation and to monitor national health risks. EPA applies TRI as a baseline to measure emission reductions mandated by the Clean Air Act Amendments of 1990. TRI also is used to monitor compliance with other laws, to target areas where enforcement of other regulations is needed, to gauge the need for additional regulatory efforts to clean up water, air, and solid waste problems, and to develop strategies for assessing pollution prevention programs.

TRI is important to the education of the community regarding facilities and potential hazards in the local area. National newspapers, including *USA Today*, the *New York Times*, and the *Wall Street Journal,* as well as regional newspapers and scores of trade and labor union publications, have run stories on TRI findings and the effectiveness of the right-to-know statute.

Academics rely on TRI data for environmental research and education. For example, the Environmental Studies Program at Dickinson College in Pennsylvania requires its students to prepare toxic waste audits on communities or facilities, using TRI as a resource. TRI reports are often pivotal in studies of chemical use and in the development of alternative technologies for preventing toxic releases.

What do TRI data show?

To date, there have been very significant reductions in the pounds of TRI chemicals released to the environment. From 1988 to 1997, on-site air releases of "core" TRI chemicals (those which have had no change in their reporting requirements since TRI's inception in 1987) decreased by 55 percent in terms of weight. Reductions in the reported releases of TRI chemicals to air were greatest in the earlier reporting years. In many cases, the "low-hanging fruit" has already been picked, and the expenditures required to reduce emissions further will be commensurately higher. Yet the quantities of toxic chemicals released to the environment in the U.S. are still quite significant. In 1997, facilities reported that 1.3 billion pounds of TRI toxic chemicals were released into the air; on-site releases to all pathways plus off-site waste transfers amounted to 5.8 billion pounds.

Chemical releases and risk

TRI data on the quantity of emissions alone do not reveal the extent to which public health is at risk. The evaluation of risk requires consideration of not only how much of a chemical is released, but also the toxicity of that chemical and the dose associated with that release.

The toxicity of the TRI chemicals varies greatly; the human health impacts of the various carcinogens and noncarcinogens in the inventory can differ by up to seven and eight orders of magnitude, respectively. That is, a single pound of one of the most toxic chemicals, such as acrolein or methyl isocyanate, is toxicologically equivalent to one hundred million pounds of the least toxic of these substances.

From a public policy perspective it is also important to have knowledge of the number of individuals exposed. All things equal, e.g., dose and toxicity, a greater number of exposed individuals may justify a risk-reduction initiative. When "other" factors are not equal, decisions become less well defined. The human health effects of some TRI chemicals depend upon the exposure pathway. Friable asbestos, for instance, is a highly potent carcinogen when exposure occurs via inhalation, but it is not considered toxic when ingested. And from a risk-screening standpoint, variations in the number of individuals exposed are a major concern.

These factors can have a major impact on the ranking of risks associated with TRI releases. Table 1 compares the rankings of the 50 U.S. states (plus Washington DC, Puerto Rico, and the Virgin Islands) for total air releases of TRI chemicals in 1997 to air from three perspectives: the quantity of pounds released; the hazard associated with those releases, obtained by incorporating chemicals' toxicity weights; and the resulting risks to human health, incorporating dose and the size of the receptor population. The consideration of chemical releases from hazard-based and risk-related perspectives re-aligns state rankings considerably. Utah, for example, ranks fifth in the U.S. in sheer pounds of airborne releases, 19th from a hazard-based perspective, but only 37th from a risk-related perspective. The sparse population in much of the state drives down the latter ranking. For example, a single facility in Utah had the highest quantity of air releases of TRI chemicals in the country, but because no one lives within 30 kilometers of that facility, these releases have minimal risk-related impact on human health. Pennsylvania, on the other hand, ranks 14th in terms of pounds released, but fifth in terms of hazard and third in terms of risk.

Table 1: Rankings based on air releases of TRI chemicals in 1997[a]

Pounds			Hazard		Total Risk	
Rank	**State**	**Percentage**	**State**	**Percentage**	**State**	**Percentage**
1	TX	8.10%	OH	9.30%	OH	10.70%
2	TN	6.20%	SC	9.30%	IL	9.90%
3	LA	5.60%	MO	8.30%	PA	8.00%
4	OH	5.00%	TX	7.70%	TX	6.80%
5	UT	4.90%	PA	5.80%	IN	5.70%
6	IL	4.90%	IL	5.10%	MO	4.60%
7	AL	4.70%	IN	4.70%	CA	4.50%
8	IN	4.30%	AL	3.40%	MI	4.50%
9	NC	3.90%	MI	3.20%	AL	4.20%
10	GA	3.60%	NC	3.00%	NJ	3.90%
11	VA	3.60%	LA	2.90%	SC	3.80%
12	MI	3.30%	TN	2.90%	WI	3.30%
13	SC	3.30%	WI	2.60%	TN	2.80%
14	PA	3.00%	AR	2.50%	NY	2.70%

Table 1: Rankings based on air releases of TRI chemicals in 1997[a]

Pounds			Hazard		Total Risk	
Rank	State	Percentage	State	Percentage	State	Percentage
15	MS	2.90%	GA	2.20%	GA	1.90%
16	KY	2.60%	IA	1.80%	KY	1.80%
17	MO	2.50%	KY	1.70%	LA	1.70%
18	FL	2.40%	NY	1.60%	WV	1.70%
19	CA	2.30%	UT	1.60%	AR	1.50%
20	WI	1.90%	NJ	1.50%	IA	1.20%
21	AR	1.90%	AZ	1.50%	NC	1.20%
22	IA	1.80%	OR	1.40%	MA	1.10%
23	NY	1.80%	MA	1.30%	AZ	1.10%
24	WA	1.60%	MS	1.30%	CO	1.10%
25	KS	1.50%	CA	1.20%	VA	1.00%
26	OK	1.40%	KS	1.10%	KS	0.90%
27	OR	1.30%	MT	1.00%	MS	0.80%
28	MN	1.30%	VA	1.00%	WA	0.80%
29	WV	1.10%	FL	1.00%	OR	0.80%
30	NJ	0.70%	WV	0.90%	FL	0.80%
31	AZ	0.70%	NM	0.90%	MT	0.70%
32	MD	0.60%	OK	0.80%	OK	0.70%
33	NE	0.50%	WA	0.80%	NE	0.60%
34	PR	0.50%	MN	0.70%	CT	0.60%
35	ME	0.50%	NE	0.60%	MN	0.50%
36	MA	0.40%	MD	0.60%	NH	0.50%
37	CT	0.40%	CO	0.50%	UT	0.40%
38	ID	0.40%	ME	0.50%	DE	0.40%
39	MT	0.30%	DE	0.40%	MD	0.30%
40	AK	0.30%	NH	0.40%	NV	0.20%
41	CO	0.30%	CT	0.30%	NM	0.10%
42	DE	0.20%	NV	0.20%	ME	0.10%
43	NM	0.20%	ID	0.20%	PR	0.10%
44	WY	0.20%	WY	0.10%	ID	0.10%
45	SD	0.20%	SD	0.10%	RI	0.10%
46	NH	0.20%	PR	0.00%	WY	0.00%
47	ND	0.10%	RI	0.00%	SD	0.00%
48	RI	0.10%	ND	0.00%	ND	0.00%
49	NV	0.10%	AK	0.00%	HI	0.00%
50	VI	0.10%	VT	0.00%	VT	0.00%
51	HI	0.00%	VI	0.00%	AK	0.00%
52	VT	0.00%	HI	0.00%	VI	0.00%
53	DC	0.00%	DC	0.00%	DC	0.00%

[a] No air releases were reported for Guam (GU) in 1997. Although there were air releases reported for American Samoa (AS) in 1997, no population data has yet been incorporated into the RSEI model for AS and GU. Therefore, these two U.S. Territories are not included in these results. In addition to the 50 states. data are presented here for Washington, DC, Puerto Rico (PR), and the US Virgin Islands (VI).

The EPA's Risk-Screening Environmental Indicators Project

The EPA's Risk-Screening Environmental Indicators (RSEI) model incorporates information on chemical toxicity, exposure ("dose"), and the size of the exposed general population.[3] This model was used to calculate the state-level rankings reported in Table 1; it can similarly generate risk indicators on a chemical-, facility-, geographic-, and media-specific basis. Currently, TRI is the primary source of chemical release data used in the RSEI model.[4]

Most studies of toxic releases have skirted the question of risk, generally treating all chemical releases as equally dangerous (Brajer and Hall 1992; Glickman and Hersh 1995; Kriesel *et al.* 1996; Perlin *et al.* 1995; Riley *et al.* 1993; Stockwell *et al.* 1993). Although some researchers have begun to weight emissions for toxicity (Arora and Cason 1999; Bowen *et al.* 1995; Brooks and Sethi 1997; Horvath *et al.* 1994), they generally have not extended the concern with risk to the issue of dispersion of chemicals from their sources to the receptor populations. Instead, most use a singular threshold distance to measure risk.[5] As Arora and Cason (1999) concede, most researchers "do not attempt to analyze exposures as it would entail very elaborate mappings using the census tract and a geographical information system." Yet practitioners involved in risk analysis in specific towns and local regions consider information on chemical dispersion to be essential. The crude approach of most researchers on this question has often led to a discounting of their results in the scientific and regulatory community.

Full-scale risk assessment is complicated and can require data that are not always available. However, risk can be analyzed with varying levels of completeness. Risk-screening approaches consider some or all of the factors associated with formal risk assessment, without attempting to address every detail that would be needed for a complete picture. In the case of the TRI data, such approaches fall along a continuum ranging from the simplest depiction of "risk," in terms of pounds of chemicals released to the environment, to the most sophisticated characterization offered by a formal risk assessment. The hazard-based perspective, which considers only the pounds of chemicals released and their toxicity, is the next step along this continuum. To evaluate the degree to which people are exposed to the chemical (that is, the dose at a given location and the size of the population exposed), several models use surrogate (or "proxy") information, such as proximity to a facility discharging chemicals to the air. This approach does not account for such important considerations as stack height, wind patterns, a chemical's decay in air, or pathway-specific toxicity. Unlike other tools, the RSEI includes substantial site-specific information, placing it closer to the formal risk assessment end of the continuum.[6]

To estimate the relative risks to chronic human health in the U.S. posed by toxic chemical releases, the model integrates toxicity weights for individual chemicals and chemical categories and exposure estimates, based upon pathway-specific reporting of releases to air, water and land and the size of the potentially exposed general residential population. The result is not a detailed, quantitative risk assessment, but a screening-level, risk-related perspective for relative comparisons of chemical releases.

The toxicity weights, which are directly proportional to a chemical's toxicity value, are assigned separately for the oral and inhalation exposure pathways, and include both cancer and non-cancer effects.[7] Chemical release data from TRI and pathway-specific fate and transport models, accounting for such factors as wind patterns and stream flow, are used to calculate the doses to which people may be exposed. For example, the Industrial Source Complex Long-Term model estimates concentrations for air releases in each square kilometer within a 101-kilometer by 101-kilometer grid in which a facility is centered. For these purposes, the entire country is divided into an array of one-kilometer square cells, with each facility assigned to one cell. Populations are also assigned to these grid cells, based upon relevant latitude and longitude coordinates. The model uses block-level 1990 Census data (the finest resolution of population) updated using annual county-level data. The summed, risk-related value for all of the grid cells in the 101-kilometer by 101-kilometer grid in which a facility is centered is referred to as an "indicator element" for that facility.[8] An indicator element is calculated for each combination of facility, chemical, and release pathway (air and water). Approximately three million indicator elements, representing all combinations of facility-chemical-medium, are generated and stored for the eleven years (1988-1998) of TRI reporting data.

The RSEI model allows indicator elements to be rapidly combined by chemical, release pathway, geographic area (national, EPA Region, state, county, city, or zip code), industrial sector (2-, 3- or 4-digit Standard Industrial Classification code levels), facility, or by combinations of these and other variables. Analyses using these variables can evaluate a myriad of release and exposure scenarios, in most cases using 5 to 20 minutes of computing time. The indicator values that correspond to these combined indicator elements (e.g., for all the chemicals released to air by a given facility in a given year) are unitless numbers, designed to be used for comparative purposes. The output is presented not only from the full risk-related perspective, but also from the pounds-based and hazard-based perspectives, allowing users to assess what factors are contributing most to potential risk-related impacts.

Unlike formal risk assessments that require weeks, months or, in some cases, years of technical and scientific staff time to perform, RSEI can answer many crucial questions at a screening-level in a matter of hours. This type of tool can be used first to evaluate and compare the potential impacts of toxic chemicals. The results can (and should) then be supplemented by additional analyses if necessary, e.g., what is the nature of reporting for the specific chemical category, or in some instances, the valence state of the chemical, since RSEI makes conservative assumptions regarding these substances. By allowing follow-up studies to focus, from the beginning, on initiatives that have the greatest risk-reduction potential, RSEI can substantially improve the efficiency of the resources expended.

Providing Information to Citizens and Communities

Generating risk-related information is not enough; this information must be made available to citizens and communities if they are to assess the risks they face and take action to reduce toxics in their communities. In the course of its development, the

Indicators Project has been presented to a large and diverse set of interested parties from the public and private sectors. The RSEI tool on CD-ROM has been subject to several rounds of “beta testing” (reviewing the model for errors, ease of use, etc.) by a wide audience of potential users. After receiving Freedom of Information Act (FOIA) requests for the RSEI model from the Environmental Defense Fund (EDF) and the Bureau of Environmental News of the Bureau of National Affairs, Inc., EPA decided to make the model publicly available. Since July 1999, approximately 1500 copies of the RSEI CD-ROM have been distributed to EPA Offices and Regions,[9] TRI Regional and State Coordinators, members of Congress, other federal and state agencies, environmental organizations, public interest groups, industry, law firms, educational institutions, the press, and citizens at large.

The RSEI model has been designed to be user-friendly. EPA facilitates its application by providing a user’s manual, extensive context-sensitive help screens built into the software, an internet home page, and direct help to users via e-mail or telephone. To promote proper interpretation of the model’s results, extensive documentation of its strengths and limitations are provided in the model itself, the user’s manual and the home page. The Agency has also developed a training program for its Headquarters and Regional staff and interested state personnel. As the audience requesting the model widens, options for additional training, including internet-based “distance learning,” are now being explored.[10]

Using RSEI for disparate impacts analysis

When considering negative externalities such as pollution, it is necessary to determine not only the magnitude of the externality, but also its distribution. The latter has been the primary focus of environmental justice research, *viz.*, are there disparate impacts of toxic substance exposures along demographic lines, such as race and/or income? The data generated by the RSEI are well-suited to analyze this issue. Earlier disparate impact analyses have been hampered by the lack of risk-related information available at a level of resolution that can be correlated with relevant demographic characteristics of the exposed population. In the next section, we evaluate nation-wide TRI on-site air releases using data from the RSEI model.[11] This national perspective suggests whether these groups suffer disparate impacts as a whole, and can serve as a model for others to perform regional or local disproportionate impact analyses to help identify hot spots of potential environmental justice concern.

The indicator elements generated by RSEI not only account for many of the factors relevant to risk, but do so on the basis of a 1-km-by-1-km spatial resolution.[12] This degree of spatial resolution is particularly useful for disparate impact analyses, as grid cells of this size can be aggregated to any level in order to analyze the geographic area of interest (e.g., census block or block group, census tract, zip code, etc.).[13] Approximately 10 million grid cells represent the U.S. and its territories. Of these, in 1996, approximately 773,000 grid cells were impacted by on-site TRI air releases; that is, these cells had both an estimated dose and people living within the cell.

The race and income data used in the analysis below are drawn from the approximately seven million census blocks and 230,000 census block groups delineated by the 1990 Census. Blocks and block groups represent the smallest geographic units for which census information is available.[14] Unlike the indicator's stable grid cell size, census blocks and block groups vary in size, depending upon the urban or rural setting in which they are located. In sparsely populated rural settings, blocks and block groups may be many times larger in area than the 1-km x 1-km grid cells used in the model and, conversely, in a heavily populated urban setting, several blocks or block groups may be associated with a single grid cell.

National Environmental Justice Analysis Using RSEI

In this section, the cell-by-cell data generated by the Risk-Screening Environmental Indicators are combined with relevant census information to analyze the disparate incidence of risk-related impacts from toxic chemical releases to air for areas located near manufacturing facilities reporting TRI emissions for 1996. The analysis is not intended to represent an accounting of the costs or benefits of living in areas associated with higher or lower risk-related cell scores.[15] Instead, this research represents the first time that potential disparate impacts are tested along this vector of environmental medium with a carefully designed risk-related measure. We find considerable differences in estimated impacts among geographic areas. For this reason, we pay specific attention to systematic differences between those areas with the highest risk-related cell scores and the other areas affected by TRI emissions.

Following a discussion of methodological issues, we report an analysis of the difference in means between the top risk-related decile and the rest of the sample. The difference-of-means analysis provides an indication of the association between risk-related scores and each of the racial, ethnic origin, and socio-economic groups considered, without controlling for the independent effects of each other factor. We follow the difference-of-means analysis with a multivariate regression analysis that controls for the independent effects of other neighborhood demographic characteristics. The multivariate regression analysis better controls for potentially confounding relationships among different demographic variables.

Methodology

The RSEI indicator elements represent the sum of all affected grid cells on a facility-by-facility basis. For the purpose of this analysis, however, we generated a separate RSEI database representing the *aggregated* risk-related impacts of all nearby facilities on a cell-by-cell basis. To study the relationship between relative risk and community profiles, we matched these "cell scores" with census data pertinent to poverty and environmental justice concerns.

Our research question is whether risk from air-borne chemical emissions is associated with race, Hispanic-origin, and socioeconomic make up: that is, are some groups disproportionately predominant in areas with large exposures to chemical emissions? To answer this question, we must consider how best to factor in the overall density of people in an area.

The risk-related score for each square-kilometer cell is based not only on the amount and toxicity of TRI air releases to which people residing in that cell are exposed, but also on the number of people living there: all else equal, cells with a higher population density will have a higher risk-related score. Difference-of-means comparisons based on those scores provide an accurate indication of how remedial policies based on the RSEI model would impact environmental justice concerns, but the apparent differences among demographic groups could be due, in part, to the fact that some tend to live in more densely populated areas. To assess the extent to which this affects our results, we also present a difference-of-means analysis from a non-population weighted risk-related perspective, in which population density does not affect the cell scores.[16]

The primary demographic characteristics we analyze are race, Hispanic-origin (ethnicity), and socioeconomic class.[17] We explore the expectation that minorities will be found in higher proportions in higher risk areas, due to choices by facilities regarding emission processes or siting; or to choices by potential residents regarding neighborhood selection; or some combination of the two.[18] Socio-economic class is characterized, as typically is done in the environmental justice literature, by including median per capita income (in $1,000 units), the percentage of people below the poverty line, and the proportion of the work force that are unemployed. There are two potential and contrasting expectations regarding the association between income and risk. On the one hand, higher incomes in a community could lead to direct or indirect pressure on nearby facilities to decrease pollution or shift emissions to other facilities, resulting in a negative correlation. On the other hand, a larger manufacturing base could lead to higher incomes as well as higher emissions and higher populations, resulting in a positive correlation.

We also examine the differences in the percentages of adults with college-level education and those not completing high school. The expectation from an environmental justice perspective is that those with lower educational achievement may be located in greater proportions in areas with higher risk-related cell scores.

Finally, we also explore whether certain age groups are disproportionately represented in places exposed to high levels of airborne emissions. Because older residents and children may show particular sensitivities to airborne hazards, we examine the proportions above age 64 and below age 18.

There are several limitations of Census data for this type of study. All demographic data are self-reported responses. The selection of one category that best describes the respondent's identity may pose particular problems for the racial or ethnic-origin variables for multi-racial respondents.[19] The demographics from the 1990 Census are available and measured at the block level, with the exception of the median income and unemployment variables, which are available only at a higher level of aggregation known as the block-group.[20] Median income is the only demographic variable not measured as a percentage.

To allow easier interpretation of the RSEI risk-related scores used in our analysis, the score for each grid cell is divided by the mean score for all cells, so that the new mean score is one. These "centered" risk-related scores therefore are defined relative to the average for all cells impacted by TRI-reporting manufacturing facilities.

Descriptive statistics for the risk-related cell scores for the entire sample are reported in Table 2. A notable feature of these data is their extreme skewness. The vast majority of the centered risk-related scores for individual grid cells fall between zero and one, but a much smaller number of grid cells have risk-related scores up to thousands of times higher than either the average or the median. The average relative risk score in the top decile of cells is 320 times that found in the rest of the sample. Because of these extreme variations, we focus below on the demographic differences between the areas of highest risk and the other areas. Descriptive statistics for the Census demographics, as measured at the level of square kilometer cells, are provided in Appendix Table 1.

Table 2: Descriptive statistics of population-weighted risk-related cell scores, all cells, 1996

Category of cells	Mean	Standard deviation	Skewness	Median	Minimum	Maximum
All cells	17.74	300.73	86.48	0.036	7×10^{-11}	65059
All cells (centered)	1.00	16.96	86.48	0.002	4×10^{-12}	3668
Top decile (centered)	172.58	963.89	28.10	32.670	8.42	65059
Deciles 2-9 (centered)	0.54	1.32	3.48	0.205	7×10^{-11}	8.42

Notes:
N=773,068.
Centered average cell risk-related scores are "centered" by dividing by the mean value for all cells (17.74).

Difference-of-means from a population-weighted risk-related perspective

The results of the difference-in-means tests are displayed in Table 3, which compares the mean values of our demographic variables for the top risk-related cell score decile and the rest of the sample (that is, the remaining nine deciles). The third column indicates the absolute difference between the means for the top decile and the other deciles. Column four presents the overall mean for all ten deciles, and column five shows the difference as a percentage of the overall mean.[21]

The differences in these mean values suggest that there are grounds for concern regarding disparate risk-related impacts. However, the risk picture is not entirely unbalanced in favor of "advantaged" groups. The proportion of non-Hispanic whites living in cells in the highest risk-related score decile is significantly lower than in the lower-risk deciles, while the percentages of blacks, Asians and persons of Hispanic-origin are significantly higher. Asian and Pacific Islander populations show the greatest proportionate differences, but as we will see when we discuss the non-population weighted risk-related perspective, this is related strongly to their concentration in cells with high population densities. The percentages for blacks and Hispanics also are more than twice as high in the top-risk decile as in the rest of the cells. These results support the concerns of environmental justice advocates. Also in line with environmental justice concerns, the percentage of the unemployed and the proportion of young people are higher in the top-risk decile.

However, in contrast to expectations developed from environmental justice concerns, Native Americans, who are less likely to live in highly industrialized areas, represent a smaller proportion of the population in the highest risk neighborhoods than in the rest of the sample. Similarly, the proportion of those with college educations is higher in the highest risk-score decile while the proportion of those with no more than a grade-school education is lower. These results suggest that, at the national level, the propensity for personal income and education to rise with manufacturing production (and potential risk-related impacts) is stronger than the countervailing pressure from higher-income or better educated communities to reduce risk from chemical emissions.[22] In addition, the percentage of those people living below the poverty line and the proportion of elderly residents is lower in the highest risk-related cells than in the rest of the sample.

Table 3: Difference-of-means for top impact decile vs. others, from a population-weighted risk-related perspective

Demographic characteristic	Top risk decile	Other deciles	Absolute difference	Overall sample mean	Difference as % of overall sample mean
% White	83.0%	92.3%	-9.4%*	91.4%	-10%
% Black	12.4%	5.4%	+6.9%*	6.1%	+114%
% Asian & Pacific Islander	1.8%	0.6%	+1.2%*	0.7%	+166%
% Native American	0.5%	0.7%	-0.2%*	0.7%	-25%
% Hispanic origin	5.4%	2.5%	+2.9%*	2.8%	+106%
% Below poverty	12.0%	12.1%	-0.1%*	12.1%	-1%
% Unemployed	6.4%	5.8%	+0.5%*	5.9%	+9%
Median income (in $ thousands)	$32.7	$30.5	+$2.2*	$30.7	+7%
% Over 64 years old	12.9%	13.7%	-0.8%*	13.7%	-6%
% Under 18 years old	25.5%	24.9%	+0.7%*	25.0%	+3%
% Grade-school education or less	25.4%	27.6%	-2.2%*	27.4%	-8%
% College educated	18.0%	14.7%	+3.3%*	15.1%	+22%

Notes:
N= 77,307 for top decile; 695,761 for rest of sample.
*Difference is statistically significant (p<.01) using two-sample t-test with unequal population variance and using two-sided hypothesis tests.
Due to rounding, percentages within variable groups may not add up to 100 and differences in decile medians may not appear correct.

Overall, the difference-of-means tests present a mixed set of findings regarding relative risk-related impacts from TRI-reporting facilities upon demographic groups of environmental justice concern. There are substantially higher proportions of Asian and Pacific Islanders and blacks relative to whites in the top-risk decile, and of Hispanics relative to non-Hispanics. However, the income and education demographic characteristics show weaker patterns of inequity or relationships reversed from that which might be expected.

Difference-of-means from a non-population-weighted risk-related perspective

To examine the extent to which the differences in risk reported above are due to differences in population density, we perform a similar analysis from a non-population-weighted risk-related perspective. That is, we exclude the population-weighting factor of the RSEI model and estimate the risk-related potential present in a cell regardless of population. For this purpose, the cell scores are calculated only from the aggregated

Table 4: Difference-of-means for top impact decile vs. others, from a non-population-weighted risk-related perspective

Demographic characteristic	Top risk decile	Other deciles	Absolute difference	Overall sample mean	Difference as % of overall sample mean
% White	87.9%	91.8%	-3.9%*	91.4%	-4%
% Black	9.4%	5.7%	+3.7%*	6.1%	+54%
% Asian & Pacific Islander	0.8%	0.7%	+0.1%*	0.7%	+7%
% Native American	0.6%	0.7%	-0.1%*	0.7%	-16%
% Hispanic origin	3.0%	2.7%	+0.3%*	2.8%	+8%
% Below poverty	12.7%	12.0%	+0.7%*	12.1%	+5%
% Unemployed	6.4%	5.8%	+0.5%*	5.9%	+9%
Median income (in $ thousands)	$30	$31	$-1*	$31	-3%
% Over 64 years old	13.7%	13.7%	-0.0%	13.7%	-0%
% Under 18 years old	24.9%	25.0%	-0.1%	25.0%	-0%
% Grade-school education or less	27.8%	27.4%	+0.4%*	27.4%	+1%
% College educated	14.2%	15.1%	-0.9%*	15.1%	-6%
Population density (persons/km^2)	480	237	+244%*	261%	+93%

Notes:
N = 77,307 for top decile; 695,761 for rest of sample.
*Difference is statistically significant (p<.01) using two-sample t-test with unequal population variance and using two-sided hypothesis tests.
Percentages within variable groups may not add up to 100 and differences in decile medians many not appear correct due to rounding.

chemical concentrations adjusted by toxicity and exposure considerations, without considering the number of people residing in a cell. The results are presented in Table 4.

In general, this non-population-weighted perspective shows somewhat smaller differences in the proportion of minorities in the top risk-score decile than did the population-weighted risk-related perspective. Nevertheless, the percentages of blacks, Hispanics, and Asians in the top-risk-potential neighborhoods remain significantly higher than in the rest of the areas. The difference is particularly striking for blacks, suggesting that the disproportionate impacts to which African-Americans are exposed are not associated only with their residence in high population density locations.

Multivariate regression analysis

In this section we use multivariate regression analysis to explore whether certain demographic groups are over-represented among the geographic units with the highest risk-related indicator scores after controlling for the independent effects of other demographic factors. This multivariate analysis of risk incidence uses probit techniques to perform dichotomous dependent variable analyses. Probit regression models divide the item to be explained into two values or groups – in this case, cells that are in the highest quintile (20 percent) of RSEI scores and those that are not. The analysis focuses on what demographic and socioeconomic variables affect the probability of being in one of the two groups.

Due to the construction of the indicators to include population weighting, locations with high and low population densities may have different estimated coefficients (as indicated by Chow tests). Therefore, we analyze separately those areas that are densely populated and those sparsely populated, as defined by whether the population density is above or below 100 persons per square kilometer. Descriptive statistics for the variables, separated into sparsely and densely populated locations, are presented in Appendix Table 2.

Probit models reveal the change in probability of being in the selected group (in this case, the top risk-related score quintile) for hypothetical observations differing by one "unit" of a demographic characteristic, holding all other factors constant. In this study, a one-unit difference is the difference between a square kilometer cell with 0 percent of a given demographic characteristic versus an otherwise identical cell with 100 percent of that characteristic.[23] The exception is median income, for which the probit results indicate the change in probability of being in the top quintile for a cell with a median income of $40,700, versus one with the average median income of $30,700.[24] To ease interpretation, all other demographic characteristics are held at their mean values when calculating the effects of each variable.

The results of the probit analysis are summarized in Table 5. (Since probit regression models are non-linear, the changes associated with the coefficients vary by the starting value; Appendix Table 3 presents the original coefficients and their standard errors.) Table 5 shows that Asians, Blacks, Hispanics, and the unemployed exhibit the strongest positive associations with the RSEI risk-related indicator scores in densely populated areas. In contrast, the population under the age of 18 and the proportion of adults lacking high school education exhibit negative relationships. These results are roughly consistent with those found using the uncontrolled tests of differences in means examined earlier.

Table 5: Probit of top risk-related score quintile, 1996

(Percent change in probability a cell is in top quintile, based on 100% differences in demographic characteristics between cells)[a]

Demographic characteristic	Densely populated	Sparsely populated
% Below poverty	–2.7%	–0.9%
% Unemployed	21.6%	20.2%
Median income [b]	6.8%	55.7%
% Black	19.6%	–0.8%
% Asian & Pacific Islander	52.3%	4.8%
% Native American	–2.4%	5.0%
% Hispanic origin	11.6%	–1.4%
% Over 64 years old	–0.6%	–0.2%
% Under 18 years old	–9.5%	3.1%
% Grade-school education or less	–5.5%	–5.0%
% College educated	–0.4%	–0.1%
N	241,307	531,761

Notes:

a For instance, in densely populated areas, the model indicates a square kilometer cell with 100 percent unemployment (column one, row two) is predicted to be 21.6% more likely than a cell with 0 percent unemployment to be in the top risk-related indicator score quintile. For the median income variable, the coefficients represent the change in the likelihood that a cell will be in the top risk-related indicator score quintile, if the median income in the cell were $10,000 higher than the average median income of all cells.

b These figures include the combination of a linear and a squared term.

If one compares hypothetical cells in densely populated areas that contain 0 percent Asians to ones that have 100 percent Asian population, the predicted probability of being in the top risk-related score quintile rises by 52.3 percent (holding all other demographic characteristics at their mean values). In more sparsely populated areas, the results show a smaller 4.8 percent increase in the probability of being in the top quintile comparing cells representing 0 or 100 percent Asians.

For the largest minority group, Blacks, the probit model predicts that areas with a 100 percent Black population have a 19.6 percent higher probability of being in the top quintile than those with 0 percent in densely populated areas. The relationship between proportion Black and the probability of being in the top quintile is negative but very small in sparsely populated areas.

The probit models predict that densely populated areas that are 100 percent Hispanic would be 11.6 percent more likely than 0 percent Hispanic areas to be in the top risk quintile. In sparsely populated areas, 100 percent Hispanic cells would have a slightly lower probability (than 0 percent Hispanic cells) of being in the top risk quintile. The relationship is the opposite for Native American areas: the probit model estimates a negative relationship of 2.4 percent in densely populated areas, but a positive relationship of 5 percent in sparsely populated areas.

The estimated relationship between median income and the probability of being in the top quintile is U-shaped, becoming positive as the difference in median income becomes larger further from the mean. In densely populated areas, a difference in median income of $10,000 above the average is estimated to increase by 6.8 percent the probability of being in the top quintile. This relationship appears to be even stronger in more sparsely populated areas of the country, where a $10,000 increase in median income is associated with a 55.7 percent increase in the probability of being in the top quintile of risk cells, all else equal. These results run counter to the traditional relationship expected between risk and median income.

In contrast, the probit model gives more intuitive results for unemployment. The probit model predicts 100 percent unemployment to increase the probability of being in the top quintile by about 20 percent relative to areas with no unemployment. This result holds in both sparsely and densely populated areas, and it represents the largest relationship between risk-scores and a demographic characteristic found in more sparsely populated areas.

The probit model estimates a negative relationship between the likelihood of being in the top risk-score quintile and the prevalence of poverty in a cell; a negative relationship also holds for the proportion of adults lacking a high-school education. These results, like those from income, run counter to the expectation that these groups would face higher risks.[25]

In sum, the results of our multivariate analysis suggest that, holding the values of other variables constant, in densely populated areas the proportions of Asians, Blacks, Hispanics, and the unemployed have the largest impacts on the probability of being in the top risk-related score quintile, findings consistent with environmental justice concerns. In sparsely populated areas, unemployment again has a strong impact in the expected direction, but income shows a counter-intuitive effect.[26]

Table 6 mirrors Table 5, but adjusts for the variation found within the sample by using a one-standard-deviation difference from the mean, rather than a 100 percent difference, in the demographic characteristic, to predict the change in probability of being in the top risk-related score quintile.[27] In each case, if one examines a standard deviation change in the demographic characteristics of the square kilometer cells, the predicted change in probability of being in the top risk related score quintile is fairly small. The largest increase in densely populated areas is for Blacks at about 3.4 percent. That is, all else held equal, a shift of the proportion of Blacks of 20 percent (one standard deviation) in more densely populated areas is predicted to raise the probability a cell is among the top quintile in risk-related scores by 3.4 percent.

Table 6: Probit of top risk-related-score quintile, 1996
(Percent change in probability a cell is in top quintile, based on one-standard-deviation difference in demographics between cells)

Demographic characteristic	Densely populated	Spa popu
% Below poverty	–0.3%	0.1%
% Unemployed	0.8%	0.8%
Median income [a]	–3.7%	–4.5%
% Black	3.4%	–0.3%
% Asian & Pacific Islander	1.6%	0.5%
% Native American	–0.1%	0.9%
% Hispanic origin	1.3%	–0.3%
% Over 64 years old	–0.1%	–0.0%
% Under 18 years old	–4.7%	0.7%
% Grade-school education or less	–1.7%	–1.7%
% College educated	–0.1%	–0.0%
N	241,307	531,761

Notes:
a Median income is measured in $10,000 units. This figure includes both a linear and a squared term.

RSEI as a Tool for Change

The preceding analyses use a nation-wide database generated by the RSEI model to assess environmental justice concerns with respect to TRI air releases. Such national-level analyses can help to identify disproportionate impacts on minorities, but to take this information and act upon it will require additional investigative efforts focusing on specific geographic areas. Properly identifying those sources of releases that present the greatest risk to the general public, or a disparate risk to specific population subgroups, is a particularly important challenge – one that the RSEI model can help to meet. Presently, decisions regarding policy and enforcement priorities are made either with inappropriate data (e.g., pounds of emissions) or with expensive and time-consuming risk assessments typically conducted on an *ad hoc* basis. RSEI helps resolve these issues by providing a fast and inexpensive risk-screening tool for targeting purposes.

As described previously, the indicator elements generated by the RSEI model can be combined in a variety of ways to provide additional analytical capabilities. For example, drawing upon the findings described in the disparate impact analysis, and utilizing race- and income-specific indicator elements, RSEI could be used to provide relative rankings of all zip codes within the counties or cities of southern California. Furthermore, the model could be used to identify the facilities, air exposure pathways, and chemicals of greatest concern.[28] By comparing the changes in each year's indicator values, starting with the base year of 1988, one can use RSEI to obtain a risk-related perspective on trends in environmental well-being, which can then be related to policies, socio-economic variables, and chronic human health. The flexibility of the model also provides analysts with the opportunity to rank and prioritize facilities or chemicals for strategic planning, risk-related targeting, and community-based environmental protection.

Since RSEI is a screening-level tool, additional investigation is required to ascertain, for example, whether high rankings are associated with significant health effects. Such investigation will be complicated by the fact that TRI emissions are only one component of the chemicals that individuals are exposed to, comprising less than twenty percent of total emissions nationwide. Other major sources of exposure include mobile sources, such as motor vehicles, and indoor air emissions. And even apparently significant TRI exposure levels may require additional investigation of the chemicals and/or facilities identified as "drivers" of the relative rankings. Due to insufficient reporting information regarding chemical compounds (e.g., the precise chemicals in a chemical category) and the valence states (oxidation state) of certain metals and metal compounds, *a priori* assumptions are sometimes made for modeling purposes.[29] In those instances when uncertainties exist, it is necessary to engage the relevant facilities in a dialogue to determine the nature of their emissions, and whether remedial action is indeed warranted.

Conclusion

In this paper we have discussed an approach to generate and disseminate information to those interested in environmental justice issues in a relatively sophisticated, quick and inexpensive fashion. We also have presented the results of a nationwide analysis of data generated by the RSEI model to assess environmental justice concerns with respect to TRI air releases.

Overall, the RSEI risk-related scores reveal patterns of inequity of concern to environmental justice advocates – higher risk for Blacks and Asians relative to Whites, and in densely populated areas, for Hispanics relative to non-Hispanics. They also reveal that higher unemployment is associated with higher risk. Other demographic characteristics reveal weaker patterns of inequity, or relationships reversed from those expected. The magnitude of inequities among demographic groups tends to be smaller for more sparsely populated areas.

The Risk-Screening Environmental Indicators model brings important contributions to the analysis of environmental justice issues. It can be used in a two-step fashion. First, it is used to generate a national database that provides estimates of risk-related impacts associated with TRI air releases for each square kilometer of the U.S. and its territories. The format of these data is compatible with census and proposed GIS databases. As demonstrated here, when these data are coupled with census information, it is possible to examine the relationship between these risk-related impacts and demographic variables of concern to the environmental justice community such as race, income, and age.

In the second step, the RSEI model (incorporating components to evaluate impacts at various geographic scales) is used to perform queries, based on the findings from step one, to identify geographic areas, chemicals, and facilities of particular concern. The results can be used to inform and empower citizen groups to help bring about environmental improvements, and to help correct disparate impacts. These results will aid decision makers, too, by helping to channel scarce resources to initiatives that have the greatest risk-reduction potential. The unique capabilities of this risk-screening tool will undoubtedly open other new research opportunities that can improve the health of communities across the United States. Its usefulness will expand with experience and further improvements to the model, including the ability to examine non-TRI chemicals and reporters.[30]

Disclaimer: The views expressed in this paper are solely those of the authors and do not necessarily reflect the views or policies of the U.S. Environmental Protection Agency or ICF Consulting, Inc.

Endnotes

1. In May 1997, EPA added several new industry sectors to those required to report releases: metal mining, coal mining, electric utilities, commercial hazardous waste treatment, wholesale chemicals and allied products, petroleum bulk terminals and plants, and solvent recovery services. The new reporting facilities will provide data in July 1999 for the reporting year 1998.

2. A chemical is considered to be manufactured if it is produced, prepared, compounded, or imported. A chemical is considered to be processed if it is prepared after manufacture for distribution in commerce. The term "otherwise used" means any use of an EPCRA Section 313 chemicals, including one contained in a mixture or other trade name product, or waste that is not covered by the terms "manufacture" or "process."

3. The Risk-Screening Environmental Indicators project has been on-going since 1991. During that time a substantial amount of documentation of the model has been generated. See Bouwes and Hassur (1997a, 1997b) and the Indicators Home Page at http://www.epa.gov/opptintr/env_ind/index.html.

4. While TRI reporting does not cover all toxic chemicals or sources of chemical emissions, this reporting represents one of the better and more complete databases maintained by EPA. A future version of the model will allow use of alternative databases, e.g., release information for non-TRI facilities or monitoring data for non-TRI chemicals.

5. Pollock and Vittas (1995) use a logarithmic functional form but without any reference to chemical-specific dispersion and transportation. An exception to this pattern is Hamilton (1999), who uses a commercially-available program that generates risk-related measures from TRI data. The price of such a program is out of reach for most community groups and researchers, and assumptions (e.g., nationally uniform stack heights of 10 meters) leave room for improvement.

6. The model does not provide estimates of actual risk to individuals as done in a formal site-specific, quantitative risk assessment, which incorporates *all* relevant toxicity information, exposure factors and activity patterns.

7. A chemical's oral or inhalation toxicity, or potency, is represented by reference dose and reference concentration for non-carcinogens, and oral slope factor and inhalation unit risk factor for carcinogens, respectively.

8. Note that if no one lives in a grid cell, then the estimated risk-related contribution for that cell is zero regardless of the estimated concentration.

9. The U.S. EPA structure can loosely be described as comprised of Headquarters and its Regional Offices. Headquarters is primarily responsible for policy and regulation development and the Regional Offices perform the role of intermediary between the

Agency and states and the public. Following the release of RSEI, Regional Offices requested training for themselves and their state-based constituents in the use of RSEI to insure the correct use of the model.

10. Background information, technical documents, guidance on the use of this tool, new developments, and model updates can be found on the web site for the Indicators Project (http://www.epa.gov/opptintr/env_ind/index.html). The RSEI model is designed to run on a personal computer (PC) using the Microsoft Windows 3.1 or 95/98/NT operating systems. It can be obtained from the Toxic Substances Control Act Assistance Information Service by calling (202) 554-1404 or writing to tsca-hotline@epa.gov.

11. Version 1.02 of RSEI generated the data for the analysis presented here. Version 1.02 is similar to subsequent versions, but has several differences: risk-related impacts are generated for the air pathway only; cell-by-cell impacts are estimated for a 21-km by 21-km grid, and population adjustments are made by interpolating between 1988 and 1990, and between 1997 and 1990, using annual US Census County data and US Census Decennial data, respectively.

12. The indicator elements generated by the model are defined by the summation of the risk-related impacts of the cells contained in the 101-km by 101-km grid in which the facility is centered. Since individual cells can be impacted potentially by more than one facility, cell information is further manipulated to provide aggregated risk-related impacts for each cell. The information associated with each one of these cells is stored in a temporary file. For the disparate impact analysis discussed in this paper these temporary files were generated from the cells in the 21-km by 21-km grid used in Version 1.02 of RSEI.

13. Future research efforts will investigate the influence of factors such as geographic scale of analysis and spatial autocorrelation.

14. Some environmental justice analyses have used the larger census tracts, of which there are approximately 55,000 in the U.S.

15. Benefits of living in neighborhoods studied might include factors such as the value of neighborhood amenities, proximity to places of employment, or demographic composition. Costs might include impacts on health and on the valuation of neighborhood amenities from the potential for additional health or ecological risk.

16. A drawback of exclusive reliance on a non-population weighted risk-related perspective is that the results could be unduly influenced by the presence or absence of minorities in sparsely populated areas. For example, a cell inhabited by one person who happened to be African-American (and thus the cell would be 100% black), would receive equal weight with a cell inhabited by 1,000 people, of whom 50% were African-American.

17. We follow the convention of using Census-defined terms “black” and “white” to describe those racial groups in this paper. Hispanic origin is a separate category from race on Census forms. Therefore, people self-identifying as Hispanic are included among various racial categories. The Hispanic-origin category is most highly correlated with the racial categories “white” and “other.”

18. For a discussion of siting vs. “move-in,” see Pastor (2001).

19. In the 1990 Census, people whose racial background spans more than one category could only identify one racial category. The 2000 Census will allow respondents to identify multiple racial identifications.

20. A census block is the smallest entity for which the Census bureau collects and tabulates decennial census information. It is bounded on all sides by features shown on Census Bureau maps. A block-group is a combination of census blocks that forms a subdivision of a census tract or block numbering area (BNA). A block group consists of all blocks whose numbers begin with the same digit in a given census tract or BNA.

21. Note that the overall means represent the average cell, not the share of each group in all cells taken together. For example, blacks represent only 6.1% of the population in the average cell, but a considerably larger percentage of the total impacted population by virtue of the fact that they tend to live in more densely populated cells.

22. A univariate cross-sectional (rather than time series) test is not ideal for discriminating among complicated interactions such as these. The results here are merely suggestive of which underlying interactions might predominate.

23. The reference group against which each group is compared is whatever demographic characteristic is not listed in that category. The racial categories are compared against the excluded category of “White.” Similarly, the reference group is non-Hispanics for the Hispanic-origin category, people between 18 and 64 years of age for the younger and older age categories, and adults who have at least a high school degree but have not completed a college Bachelor’s degree for the education categories.

24. Tests for non-linear relationships (i.e. relationships other than one-unit-to-one-unit changes between the risk-related scores and a demographic characteristic) indicated a quadratic (squared) relationship between risk-related scores and median income. Median income therefore is represented by both median income and its square. In Table 5 these relationships are combined for ease of interpretation.

25. Correlations among the demographic characteristics showed that in most cases there is sufficient variation to preclude multicollinearity. The exceptions are moderately high correlations between the two education variables, and between the education variables and median income or proportion below poverty. If one excludes median income and proportion below poverty from the model, the coefficients for the education variables become statistically insignificant.

26. The probit models explain only a small part of the variance in the dataset. Low predictive ability is not unusual given the large number of observations. However, it does caution researchers to remember that demographic variables characterize only a small portion of the differences in relative risk.

27. The standard deviation is calculated from the set of all cells for which the value of a demographic is not 0 percent, in order to avoid attenuation of the variance for the variables representing percent minority residents.

28. Currently, the Indicator Elements database does not permit race- and income-specific query variables, or geographic-specific queries below the zip code level. The size of a database allowing this capability would be too large to be convenient in the current CD-ROM PC environment. In the short term, this constraint could be dealt with by generating supplemental databases that have race- and income-specific Indicator Elements. In the long run, the RSEI model will be web-based, and database size will no longer be an issue.

29. TRI reporters are required to estimate only the number of pounds of the parent metal for a metals category listing, and are not required to specify the valence of these chemicals. In these instances EPA assigns the toxicity weight associated with the parent metal to metal compounds and assumes the valence state of the metal with the highest toxicity weight. This assumption is consistent with risk assessment practices at EPA of maintaining a conservative position in the absence of sufficient information, preferring to err on the side of caution, rather than possibly placing the public at risk.

30. In an effort to provide the most useful model possible, EPA encourages users to share their research efforts and suggestions for model improvements through the comments section of the RSEI Home Page at http://www.epa.gov/opptintr/env_ind/index.html, or to contact the EPA authors of this paper directly.

Appendix Table 1: Descriptive statistics of 1990 census demographics, measured as square kilometer cells

Demographic characteristic	Mean	Standard deviation	Minimum	Maximum
% Below poverty	12.06	10.68	0	100
% Unemployed	5.87	4.78	0	100
Median income (in $10,000s)	3.07	1.35	0	15
% Black[a]	6.09	18.64	0	100
% Asian & Pacific Islander[a]	0.71	3.32	0	100
% Native American[a]	0.66	4.92	0	100
% Hispanic origin[a]	2.76	10.33	0	100
% White	91.41	20.41	0	100
% Over 64 years old	13.66	16.45	0	100
% Under 18 years old	24.96	13.18	0	88
% Grade-school education or less	27.43	14.44	0	100
% College educated	15.05	12.81	0	100
Population density	261.07	756.50	1	57000

Notes:
N=773,068.
a Percentages represent averages among square-kilometer cells, not proportions of each demographic in the sample as a whole. For the racial/ethnic variables, these measures can differ greatly.
b Minimum values of zero are predominantly a function of a few cells with as few as one or two residents.

Appendix Table 2: Descriptive statistics of 1990 census demographics, measured as square kilometer cells, by population density

Demographic characteristic	Densely Populated (³ 100/km^2) Mean	Densely Populated (³ 100/km^2) Standard deviation	Sparsely Populated (<100/km^2) Mean	Sparsely Populated (<100/km^2) Standard deviation
% Below poverty	10.87	11.60	12.92	10.20
% Unemployed	5.80	5.34	6.01	4.57
Median income (in $10,000s)	3.50	1.72	2.83	1.08
% Black[b]	8.60	20.00	4.81	17.66
% Asian & Pacific Islander[b]	1.60	4.35	0.30	2.74
% Native American[b]	0.63	3.56	0.75	5.86
% Hispanic origin[b]	4.77	12.10	1.83	9.18
% White	87.23	21.62	93.38	19.46
% Over 64 years old	12.36	9.61	14.39	18.92
% Under 18 years old	26.06	7.73	24.48	15.09
% Grade-school education or less	24.17	15.36	29.11	13.69
% College educated	19.58	15.84	12.82	10.39
Population density	753.12	1175.61	26.97	24.55
Risk scores, centered[a]	1.61	18.28	0.72	15.07
Number of cells in top risk quintile	119,434		35,180	
Overall N	241,307		531,761	

Notes:

a Risk-related scores for the full sample are centered, as in Table 2.

b Percentages represent averages among square-kilometer cells, not proportions of each demographic from the sample as a whole.

Appendix Table 3: Probit of top risk-related-score quintile, 1996, estimated coefficients

Demographic characteristic	Densely Populated (³ 100/km^2)		Sparsely Populated (<100/km^2)	
	Coefficient	Standard Error	Coefficient	Standard Error
% Below poverty	–0.17***	0.03	–0.05	0.03
% Unemployed	0.80***	0.06	0.76***	0.04
Median income[a]	–0.90***	0.03	–1.65***	0.07
Median income, squared[a]	0.03	0.03	0.09***	0.01
% Black	0.74***	0.01	–0.04***	0.01
% Asian & Pacific Islander	1.59***	0.08	0.24***	0.06
% Native American	–0.15*	0.07	0.24***	0.03
% Hispanic origin	0.50***	0.02	–0.08***	0.02
% Over 64 years old	0.03	0.03	–0.01	0.01
% Under 18 years old	–1.28***	0.04	0.16***	0.01
% Grade-school education or less	–0.41***	0.03	–0.36***	0.02
% College educated	–0.03	0.03	–0.01	0.03
Constant	0.64***	0.03	–0.46***	0.02
Pseudo R^2	0.02		0.01	
N	241,307		531,761	

Notes:
All significance tests calculated using White's robust standard errors.
a For presentational purposes, median income and median income squared are measured in $100,000 increments in these two rows.
*** Statistically significant at the $p \leq .001$ level.
* Statistically significant at the $p \leq .05$ level.

References

Anselin, Luc and Anil K. Bera. 1998. "Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics," in *Handbook of Applied Economic Statistics*, edited by David Giles and Aman Ullah. New York: Marcel Dekker.

Arora, Seema and Timothy N. Cason. 1999. "Do Community Characteristics Influence Environmental Outcomes? Evidence from the Toxics Release Inventory." *Southern Economic Journal* 65(4): 691-716.

Ashford, Nicholas Al, James Victor Gobbell, Judith Lachman, Mary Mathiesen, Ann Minzner, and Robert Stone. 1993. *The Encouragement of Technological Change for Preventing Chemical Accidents: Moving Firms from Secondary Prevention and Mitigation to Primary Prevention.* Cambridge, MA: Center for Technology, Policy and Industrial Development, MIT.

Bouwes, Nicolaas W. and Steven M. Hassur. 1997a. Toxics Release Inventory Relative Risk-Based Environmental Indicators Methodology. Washington: EPA Office of Pollution Prevention and Toxics.

Bouwes, Nicolaas W. and Steven M. Hassur. 1997b. Toxics Release Inventory Relative Risk-Based Environmental Indicators: Interim Toxicity Weighting Summary Document. Washington: EPA Office of Pollution Prevention and Toxics.

Bowen, William M., Mark J. Salling, Kingsley E. Haynes, and Hellen J. Cyran. 1995. "Toward Environmental Justice: Spatial Equity in Ohio and Cleveland." *Annals of the Association of American Geographers* 85(4): 641-663.

Brajer, V. and J.V. Hall. 1992. "Recent Evidence on the Distribution of Air Pollution Effects." *Contemporary Policy Issues* 10:63-71.

Brooks, Nancy and Rajiv Sethi. 1997. "The Distribution of Pollution: Community Characteristics and Exposure to Air Toxics." *Journal of Environmental Economics and Management*

Glickman, Theodore S., Dominic Golding and Robert Hersh. 1995. "GIS-Based Environmental Equity Analysis: A Case Study of TRI Facilities in the Pittsburgh Area," in *Computer Supported Risk Management*, edited by G.E.G.Beroggi and W.A. Wallace. Boston: Kluwer Academic Publishers, 95-114.

Glickman, Theodore S. 1994. "Measuring Environmental Equity with Geographical Information Systems," *Resources*. Summer, pp. 116:126.

Hamilton, James T., 1999. "Exercising Property Rights to Pollute: Do Cancer Risks and Politics Affect Plant Emission Reductions?" Journal of Risk and Uncertainty 18(2): 105-124.

Horvath, Arpad, Chris T. Hendrickson, Lester B. Lave, Francis C. McMichael, Tse-Sung Wu. 1995. "Toxic Emissions Indices for Green Design and Inventory," *Environmental Science & Technology*. 29(2): 86A-90A.

Kriesel, Warren, Terence J. Centner, and Andrew G. Keeler. 1996. "Neighborhood Exposure to Toxic Releases: Are There Racial Inequities?", *Growth and Change*. 27:479-499.

Lavelle, Marianne. 1993. "Environment Vise: Law, Compliance," *The National Law Journal*. August 30, S1-S9.

Lynn, Frances M., Jack D. Kartez, and Cheryl Connelly. 1992. *The Toxics Release Inventory: Environmental Democracy in Action*. Washington: United States Environmental Protection Agency, Office of Pollution Prevention and Toxics, January, EPA 700-F-92-001.

MacLean, Alair. 1993. "Bigotry and Poison." *Progressive* 57(1): 14-19.

Mohai, Paul and Bunyan Bryant. 1992. "Environmental Racism: Reviewing the Evidence," in Bryant and Mohai, eds., *Race and the Incidence of Environmental Hazards: A Time for Discourse*. Boulder, CO: Westview, 163-176.

Orum, Paul. 1994. "Reports Using Toxics Release Inventory (TRI) Data." *Working Notes on Community Right-To-Know* July-August, 1-11.

Pastor, Manuel. 2001. "Building Social Capital to Protect Natural Capital: The Quest for Environmental Justice." In *Natural Assets: Democratizing Community Ownership,* edited by James K. Boyce and Barry G. Shelley. New York: Russell Sage Foundation Press.

Perlin, Susan A., R. Woodrow Setzer, John Creason, and Ken Sexton. 1995. "Distribution of Industrial Air Emissions by Income and Race in the United States: An Approach Using the Toxic Release Inventory." *Environmental Science & Technology* 29:69-80.

Pollack, Philip H. III, and M. Elliot Vittas. 1995. "Who Bears the Burdens of Environmental Pollution? Race, Ethnicity, and Environmental Equity in Florida," *Social Science Quarterly*. 76(2):294-310.

Riley, Gwen J., John L. Warren, Rachel D. Baker. 1993. "Assessment of Changes in Reported TRI Releases and Transfers Between 1989 and 1990." Research Triangle Park, NC: Center for Economics Research, Research Triangle Institute, May.

Ringleb, Al H., and Steven N. Wiggins. 1990. "Liability and Large-Scale, Long-Term Hazards." *Journal of Political Economy* 98:574-595.

Settina, Nita, and Paul Orum. 1991. *Making the Difference, Part II: More Uses of Right to Know in the Fight Against Toxics*. Washington: Center for Policy Alternatives & Working Group on Community Right-to-Know.

——. 1990. *Making the Difference: Using the Right to Know in the Fight Against Toxics*. Washington: National Center for Policy Alternatives.

Shapiro, Marc D. 2000. *The Impact of Community Characteristics and State Policy on Changes in Emissions and Risk from Toxic Airborne Chemicals*. Doctoral Dissertation, University of Rochester, Rochester, NY.

Stockwell, John R., Jerome W. Sorensen, James W. Eckert Jr., and Edward M. Carreras. 1993. "The U.S. EPA Geographic Information System for Mapping Environmental Releases of Toxic Chemical Release Inventory (TRI) Chemicals." *Risk Analysis* 13(2): 155-164.

United States Environmental Protection Agency, Office of Pollution Prevention and Toxics. 1998. "Using the Toxics Release Inventory", http://www.epa.gov/tri/triuse.htm, Washington: US EPA, April.

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The Natural Assets Project

The Natural Assets Project, based at the Political Economy Research Institute of the University of Massachusetts, Amherst, is a collaborative initiative launched with support from the Ford Foundation. The project aims to promote critical analysis and discussion of the potential for building natural assets – individual and social wealth based on natural resources and ecosystem services – to advance the goals of poverty reduction, environmental protection, and environmental justice.