Environmental Justice in the Wasatch Front

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In spite of more than three decades' research, consensus has yet to emerge on whether there are significant disparities between disadvantaged groups and the general population in the burdens of environmental health risks. The argument for the existence of environmental injustice is complicated by a wide range of methodological perspectives as well as the complexities of comparing regions where very different populations, environmental practices, economic conditions, and systems of race relations exist. This study presents analysis of one such region, the Wasatch Front region of Utah, giving particular attention to concerns with the measurement of disparities. Using 2000 U.S. Census data at the census block group level and data from the EPA's Facility Registry System, this study develops several measures of the frequency of environmental hazards in the proximity of populations. The study finds that there are very substantial disparities in the burdens of environmental hazards across the Wasatch Front in which race is the key factor, independent of income. But it also reveals very distinct relationships between disadvantaged populations and site density based on the locations of the sites. Multiple-site proximity methods are shown to be superior to unit-hazard coincidence methods as measurements of the disparities, having revealed striking inequalities that were invisible to unit-hazard coincidence.

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Environmental justice refers to the extent to which environmental issues raise concerns about unequal distribution of benefits or harms and concerns about exclusion from participation in decision-making regarding those issues.[1] A widely accepted definition is that provided by Environmental Protection Agency:

> [Environmental justice is] the fair treatment of all races, cultures, incomes, and educational levels with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies. Fair treatment implies that no population of people should be forced to shoulder a disproportionate share of the negative environmental impacts of pollution or environmental hazards due to lack of political or economic strength. (Rhodes, 2003, p. 19)

Environmental issues can present injustices in two main ways. In a distributive perspective, injustice occurs a group of people suffer disproportionately from environmental harms or are disproportionately denied environmental benefits without justification. An alternative perspective views justice from a

[1] The literature on environmental justice suffers from a somewhat odd compulsion to review the entire history of the subject and every dispute that has arisen in the field in every article that addresses the subject, leading to increasingly lengthy "citation dumps" in articles. I shall endeavor to avoid this, and refer the reader unfamiliar with the broader issues to Rhodes (2003) or Mohai and Saha (2007).

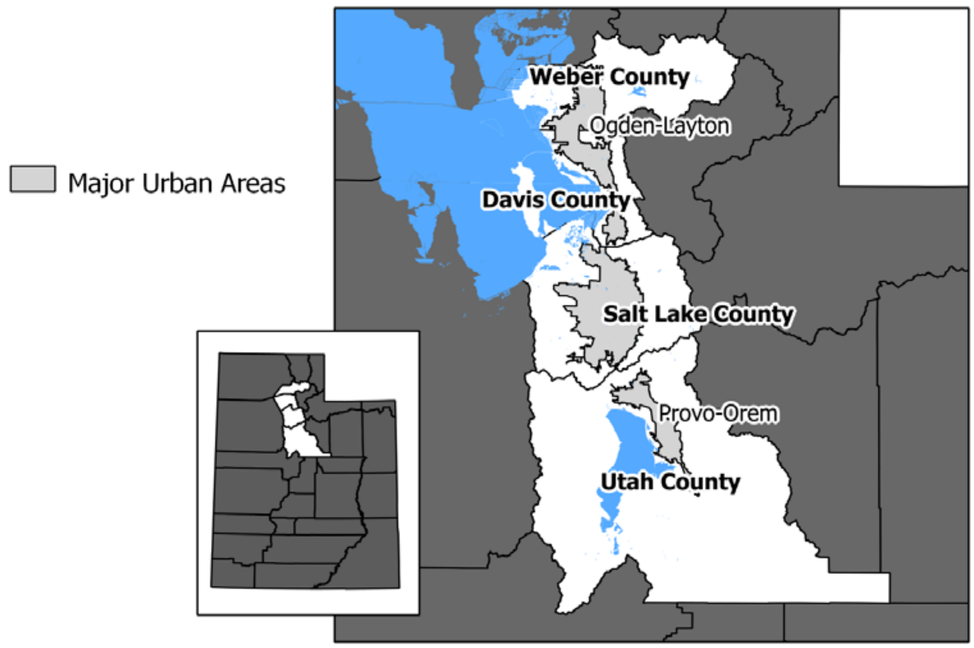

Figure 1: The Wasatch Front Region of Utah

participatory perspective, and argues that environmental justice occurs when a group of people are consistently and systematically prevented, in whole or in part, from participating in environmental decision processes. In both cases, environmental justice is concerned primarily with socially disadvantaged groups, as these are the groups most likely to suffer from environmental injustices. Environmental justice is closely related to and often synonymous (or conflated) with the concept of environmental racism. The latter is sometimes defined along the lines of the disproportionate effects approach above, though some advocates restrict the term to cases involving racial prejudice and use the terms "environmental justice" or "environmental equity" to refer to disproportionate effects with non-prejudicial causes.

The Wasatch Front (see Figure 1) has, so far, seen no substantial study of environmental disparities. The majority of the population of Utah is concentrated in the Wasatch Front region. The region follows the western slope of the Wasatch Mountains and the eastern shores of the Great Salt Lake and Utah Lake for approximately 150 km (or, according to Google maps, approximately 9.11×10^{39} Planck

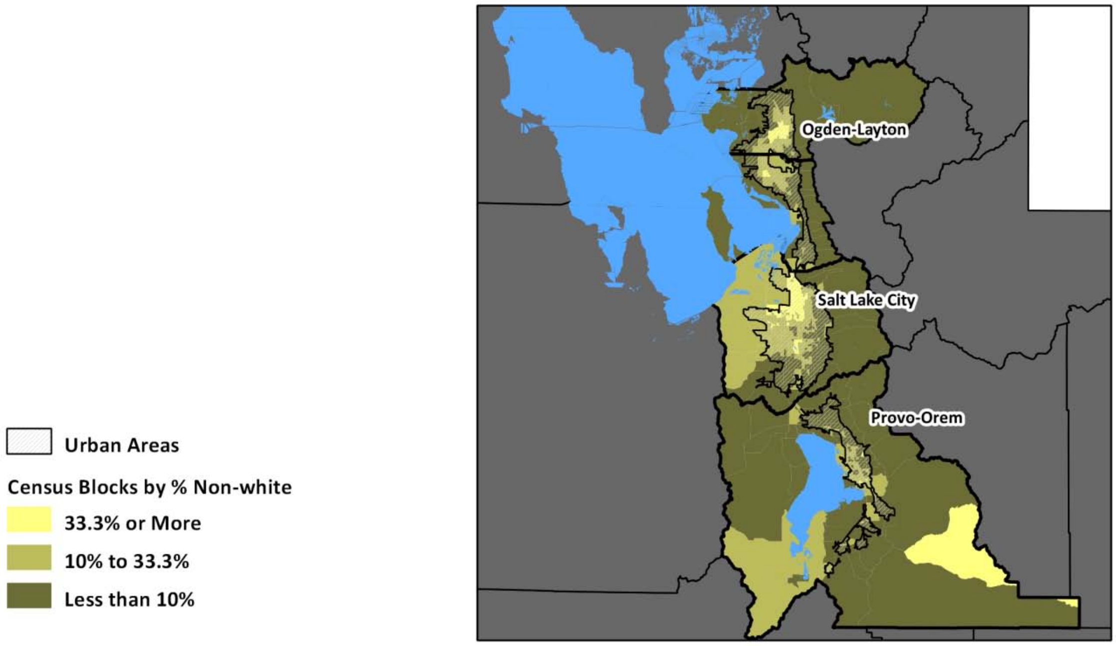

Figure 2: Census Block Groups by Non-White Population Percentage in the Wasatch Front

lengths). The 9,364 km^2 region is composed of, from north to south, Weber, Davis, Salt Lake, and Utah Counties and includes three of the four large urban areas in the state: Ogden in the north, Salt Lake City in the center, and Provo-Orem in the south. In 2009 it was home to 2.1 million –approximately 75% of the state's population. It is predominantly urban and industrial, with some agricultural areas in southern Utah county and fairly large areas of wilderness or other undeveloped land in the mountains themselves (U.S. Census Bureau, n.d.).

Like the state in general, the population of the Wasatch Front is predominantly White, non-Hispanic (80%). But this masks rather substantial concentrations of non-Whites in the Interstate-15 corridor, especially in Utah and Salt Lake Counties (see Figure 2). At 25% non-White, Salt Lake County has the highest concentration of minorities in the state with exception of sparsely populated San Juan County, much of which is part of the Navajo Nation Reservation. Utah County, by contrast, is only 15% non-White. Approximately 8% of residents are foreign born, and 13% speak a language other than

English at home; rates of both are noticeably higher in Salt Lake County. The region is generally prosperous economically, with slightly more than 9% living below the poverty level. (U.S. Census Bureau, n.d.)

MEASURING ENVIRONMENTAL JUSTICE

While the literature does address other issues (especially in political theory and philosophy), the primary question driving the empirical literature in environmental justice is methodological: how does one measure environmental burdens and the demographics of the groups who bear them in order to determine that there are, in fact, disparities? There are several dimensions to this problem, making resolution difficult and leading some to question in principle claims of environmental justice based on the poor methodological foundations of the field. Bowen and Wells offer compelling methodological critiques that lead them to dismiss claims about environmental justice them as part of a discourse that is:

> probably rooted in fear of environmentally caused disease, especially given that fear greatly surpasses the available empirical knowledge about the issue. . . . While environmental justice is a provocative political symbol, the real concerns seem to be more about power than about public health. Environmental justice appears to be largely a struggle for power, and the gap between assumption and reality a mask to hide this struggle. (2002, p. 695).

While Bowen's and Wells' rhetoric is undoubtedly as polemical as they see their opponents and their methods equally unsupported,[2] the specific critiques that they offer are compelling. Even sympathetic

[2] Bowen and Wells argue, in reviewing the environmental justice literature that they consider empirical (which appears to exclude case studies):

> Ten of the articles could be considered purely conjectural, with enough flaws in design or method to be judged useless in terms of making a contribution to the scientific literature or so insufficiently documented for the reader to know one way or the other about the contribution. Sixteen were sufficiently well designed and documented to be judged approximately accurate, but at the same time they contained notable-enough flaws that they should not have been published in a scientific journal with reasonably high standards. (2002, pp. 694-695)

assessments identify substantial difficulties in operationalizing concepts and measuring variables (Maantay, 2002; Mohai & Saha, 2007). Developing additional tools to clear a path through the methodological minefield is a major goal of this study.

The first methodological concern is how the concept of "burden" is operationalized. As Bowen and Wells argue, "lacking in the bulk of environmental justice research is a key distinction between proximity and risk. (p. 694)"; Maantay concurs that measuring the actual health risks to which a population is exposed is superior to measuring the mere presence or absence of a hazard. The difference is, substantively, less substantial that it is out to be; proximity to a hazard is best understood not as a fundamentally different concept than risk but as a quite imprecise measure of it. Even so, the argument is fundamentally sound: whether one is the victim of an injustice depends not, from most perspectives, on whether one lives near a hazard but whether one is exposed to health risks from the hazard to which others are not. A person who lives 500 meters upstream of a major water pollution source may be substantially less likely to suffer adverse health effects as a consequence than one who lives several kilometers downstream. Proximity-based models must ignore the effects of dispersion of pollutants, while risk assessment and exposure models avoid this problem.

A recent line of research (Fox, Groopman, & Burke, 2002; Morello-Frosch, Pastor, Jr., Porras, & Sadd, 2002; Buzzelli, Jerrett, Burnett, & Finklestein, 2003; Dolinoy & Miranda, 2004; Apelberg, Buckley, & White, 2005) addresses this concern, using risk assessment or exposure modeling approaches to show disproportionate distributions of risk, not just disproportionate proximity. Many take advantage of the EPA's Cumulative Exposure Project models for overall air pollution. While no study has directly com-

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However, they identify neither the articles analyzed nor the flaws present in any of the articles that lead to these conclusions. The contrast with Maantay is instructive; she provides a summary table of the articles analyzed and the methods and findings of those articles. (2002, p. 162) Thus, while the critiques of specific methods or arguments made in the literature are sound, Bowen and Wells cannot be taken as a remotely sound characterization of the literature since they does not provide any evidence to support its assertions, and the support of their arguments here should not be taken as an endorsement of their conclusions.

pared the findings of a proximity-based approach to a risk-based approach in the same spatio-temporal setting, the findings of widespread disparities using risk-based approaches tend to be consistent with those of the literature that relies on proximity-based methodologies. The former are certainly more precise and undoubtedly necessary for identifying and remedying specific injustices, and it is hard to argue that such techniques ought to be used, for instance, in identifying disparities that might arise from a project as part of environmental assessment processes. But it does not appear that the substantial additional methodological complexity of such approaches is necessarily justified by more accurate findings regarding the existence of environmental disparities in a community or region. If anything, the findings suggest that proximity-based methods should be seen as conservative estimates of environmental disparities.

The methodological complexities of risk and exposure modeling are sufficiently substantial to explain the strong preference in the literature for proximity models. But three challenges are present in analyzing disparities in the proximity of hazards to minority populations. Mohai and Saha (2007) are critical of what they term “unit-hazard coincidence” methods. This approach tests for correlation between the demographics of a particular geographic unit and the presence of environmental hazards within that unit. While this method is used exceptionally widely, Mohai and Saha argue that presence within a geographic unit is not a reliable measure of hazard proximity as it assumes that the hazard is entirely contained within the geographic unit. Where hazards are close to the boundaries of units this underestimates exposures to the hazard for those in neighboring units. The approach also does not consider variation in the size of the geographic units, which can allow for separation of hazards and populations.

The alternative, they argue, is the use of distance-based methods that measure distance from hazards to populations. This allows contrast of all demographic areas within a specified distance of a hazard with others further away. Point-containment methods represent both populations (based on surveys) and sites as points and measure distances between them. Using census data considers populations within all included census units based on a standard of either 50% areal containment of the unit or the unit centroid containment within the specified buffer around a site. It is also possible to use areal apportionment with weighting based on the portion of a unit that is included in the buffer around a site. Analyzing data nationally, they find that both the 50% areal containment and the areal apportionment methods produce results showing substantially greater inequalities than unit-hazard coincidence methods. The methods also produce great consistency across levels of geographic unit analysis, a recognized weakness of unit-host coincidence methods. Areal apportionment produced even more consistency than 50% areal containment. Such methods require the use of Geographic Information Systems for analysis but, unlike risk or exposure assessment, do not require particularly advanced modeling skills.

While this approach does represent an advance on the unit-hazard coincidence methods, it suffers from some significant limitations itself related to the unit of analysis. As Bowen and Wells argue of the literature generally, the technique of examining coincidence between areas that do and do not have hazards depends critically on the areas selected for comparison. Mohai and Saha compare the demographics within and beyond one and three mile radii of hazards nationally and find substantial differences, but this could be due to the definition of the comparison areas. As Bowen and Wells note, "a host of confounding effects associated largely with urban vs. rural areas are apt to become relevant without the researcher's awareness of them and become confounded with disproportionate distributions. (2002, pp. 692-693)" It seems plausible that this is the case with Mohai and Saha.

This is due to a unique problem in environmental justice research. Most research in the social sciences is causal, with variation in an independent variable causing variation in a dependent variable. This is not the case within the core of the environmental justice literature, which seeks primarily to demonstrate the existence of disparities rather than to identify the cause of them. As such, there is no clear dependent variable that would narrow the range of possible units of analysis. This is not the case in environmental justice research, and so the unit of analysis has often been hazards rather than populations. Studying whether the demographics of geographic units (including distance buffers) in which a hazard is located are different from the units without hazards can produce very different outcomes from studying whether units with relatively high populations of disadvantaged groups live closer to hazards that other units. Using the latter avoids the problem of selecting comparison units, as all units within the study area are included and compared on the basis of hazard proximity.

A further concern in proximity-based analysis is with density effects. In a purely distance-based model such as the Mohai and Saha method, two nearby sites could affect the same population, but would be treated identically to sites affecting two different populations. This would underestimate the health risks to the population. Dolinoy and Miranda (2004) take steps toward solving this problem in analyzing emissions of ethylene glycol monobutyl ether from the commercial lithographic printing industry in Durham, North Carolina. While their aim was to show the difference between modeling sites regulated in the EPA's Toxic Release Inventory (TRI) alone and modeling both TRI and non-TRI sites, their analysis also shows that there can be considerable overlap in exposure to pollution from individual hazard sites that should be taken into account in identifying disparities in environmental burdens. They are able to accomplish this by modeling exposure to all sites rather than just a single one. Maantay identifies studies that evaluate risks by analyzing exposure at randomized locations or that aggregate exposure at geographic unit centroids. In these cases, however, the consideration of density is used within an exposure modeling approach rather than a simple proximity model. So far, there appear to be no approaches that account for both distance and density using the far less complex proximity methodology. Ideally, measures can incorporate site and population density effects by taking into account both the frequency of and distance to hazard sites in proximity measures (as will be done below). This is another advantage of using the population as the unit of analysis; it would be far more complex to consider hazard density if the unit of analysis is the hazard itself.

In sum, recent methodological approaches suggest the utility, first, of using risk or exposure modeling in identifying disparities in environmental burdens. Where this is not possible or practical, however, proximity-based approaches are still effective measures of overall levels of disparity in a geographic region. The most effective measures rely on distance rather than coincidence between hazards and populations within pre-defined regions built for quite different purposes, use populations rather than hazard sites as the unit of analysis, and use measures that account for both the distance to and density of hazards.

METHODS OF ANALYSIS

This study primarily uses the method identified above as the preferred approach to proximity-based research in environmental justice. It begins by identifying 719 random points throughout the Wasatch Front region. Points were selected within the boundaries of U.S. Census Bureau-defined urbanized areas and urban clusters in Weber, Davis, Salt Lake, and Utah Counties. [3] For each study point, the demographics of the underlying census block group were used to estimate the probability that a hypothetical person residing at each point would hold particular demographic characteristics. Five characteristics associated with disadvantaged socioeconomic status were considered: race and ethnicity, English speaking ability, citizenship, education, and income. Each characteristic was operationalized in several ways as shown in Table 1. The same process is repeated for the census block centroids within urban areas and urbanized clusters.

[3] The selection of 750 points is sufficient to detect a 5% deviation from a hypothetical test value of 50% at $\alpha = .05$ and $\beta = .2$ with a 20% point unusability rate. Ultimately, only 31 points were eliminated because they were within 250m of another point. Limiting the selection to urban areas ensures that differences in the proportions of some disadvantaged groups in urban and rural areas will not affect the results. Since minorities in northern Utah are disproportionately urban residents, this also presents a more conservative test for disparities.

Table 1: Demographic Data Sources (U.S. Census Bureau, 2007)

Characteristic	Operationalizations	Definition	Source
Race and Ethnicity	Non-White population percentage	"Not Hispanic or Latino" respondents who answered with a race other than White, whether alone or in combination with answering White as one of multiple races, and "Hispanic or Latino" respondents	SF 1, Table P4
	Latino population percentage	"Hispanic or Latino" respondents	SF 1, Table P4
English speaking ability	Percentage who do not speak English well	Adult respondents who speak English "not well" or "poorly	SF 3, Table P19
	Percentage of linguistically isolated households	Households shown as linguistically isolated	SF 3, Table P20
Citizenship	Foreign-born population percentage	Persons not native-born citizens regardless of current citizenship (includes naturalized citizens)	SF 3, Table P21
	Non-citizen population percentage	Persons not currently citizens (excludes naturalized citizens)	SF3, Table P21
Education	High school graduate percentage	Persons at least 25 years old who are high school graduates or have any college education	SF3, Table P37
	University graduate percentage	Persons at least 25 years old with a bachelor's or higher degree	SF3, Table P37
Income	Employment Status	Unemployed civilian labor force participants at least 16 years old	SF3, Table P43
	Median Household Income	Median household income in 1999	SF3, Table P53
	Per Capita Income	Per capital income in 1999	SF3, Table P82
	Poverty status	Ratio of income in 1999 to poverty level less than 1	SF3, Table P88

These sites were then evaluated for proximity to environmental hazards. Data on environmental hazard sites is taken from the U.S. Environmental Protection Agency's Facility Registry System (FRS). (United States Environmental Protection Agency, 2011a) This system aggregates sites regulated under a wide range of federal and state information systems. FRS represents a substantial improvement over previous studies that commonly relied solely on TRI reports by centralizing all environmental hazard data (such as waste handlers and superfund sites) rather than simply the release of specific toxic substances. FRS included a total of 3,812 individual sites in Weber, Davis, Salt Lake, and Utah Counties meeting study criteria. [4] Sites were added to the GIS based on latitude and longitude references included in FRS; 290 lacked sufficient geographic information to be mapped and were therefore excluded.[5] A total of 3,522 hazard sites were included in the final data set.

[4] This analysis includes sites included in FRS under the following programs regulating sites that release or handle hazardous substances: AIRS/AFS, FRP, PCS, RCRAInfo, RMP, TRIS, and TSCA. For more information, see U.S. EPA (2011b).

[5] The FRS data includes coordinates with three different horizontal datums (North American Datum of 1927, North American Datum of 1983, and World Geodetic System of 1984) as well as nearly 300 sites with geographic coordinates but not datum information. The overwhelming majority (2,743 sites) were in NAD 1983. For those

This study uses primarily two measures of the proximity of hazards to these points. The first, a measure of hazard density only, is the frequency of hazard sites within 500 meters, one kilometer, and three kilometers of the study point. This frequency was identified by establishing buffers of the appropriate distances around each site and using a spatial join to count the number of sites within each buffer. The second measure, called the Site Exposure Index, is based on the distance to all hazard sites within 3km and given by the formula:

$$\sum \frac{1}{\ln\left(1 + \frac{d}{1000}\right)}$$

where *d* is the distance from the study point to the hazard site in meters. This creates a measure that is always positive, positively associated with proximity, accounts for both simple distance and density of sites, and reflects the presumably curvilinear relationship between distance and exposure. The SEI will be substantially distinct from simple hazard frequencies in its analytical effects if there is substantial variation in the distribution of sites within study point buffer zones.[6]

In addition to its main goal of evaluating environmental justice along the Wasatch Front communities, this study has a secondary goal of evaluating different proximity-based methods of identifying disparities. The study thus also tested unit-hazard coincidence methods and distance methods using sites as the unit of analysis. Because comparison of the areal and centroid containment methods has already established the comparability of results, this study only compared the methods used here to the simpler centroid containment method. Unit-hazard coincidence was measured at the census block group level.

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using WGS 1984, since it is considered identical to NAD 1983 at scales below 1:5,000 (National Geodetic Survey, 1995), no correction was needed. The coordinates of these sites listed using the NAD 1927 datum were converted to NAD 1983 using the National Geodetic Survey's NADCON utility (National Geodetic Survey, n.d.). Sites for which datum was unavailable were assumed to be NAD 1983.

[6] Due to errors in mapping that have not yet been fully identified, site exposure indices were not be calculated for 18 random study areas and one census block group centroid.

Table 2: Unit-hazard Coincidence

Population	Hazard	Race, Language, and Citizenship Non-White	Latino	Non-English-speaking	Linguistically Isolated	Non-citizen	Foreign-born
Block Group (N = 1,104)	Presence or Absence of Sites	Δμ = 2.73% t = 3.162 p = 0.002	Δμ = 2.1% t = 3.139 p = 0.002	Δμ = 1.12% t = 3.239 p = 0.001	Δμ = 0.96% t = 3.466 p = 0.001	Δμ = 1.33% t = 3.005 p = 0.003	Δμ = 1.56% t = 3.088 p = 0.002
Block Group (N = 1,104)	Number of Sites	r = 0.188 r^2 = 0.035 p < 0.001	r = 0.174 r^2 = 0.03 p < 0.001	r = 0.128 r^2 = 0.016 p < 0.001	r = 0.161 r^2 = 0.026 p < 0.001	r = 0.115 r^2 = 0.013 p < 0.001	r = 0.114 r^2 = 0.013 p < 0.001

Population	Hazard	Education and Income High School Graduate	College Graduate	Unemployed	Median Household	Per Capita	Poverty Level
Block Group (N = 1,104)	Presence or Absence of Sites	Δμ = -1.68% t = -2.304 p = 0.021	Δμ = -3.4% t = -3.501 p < 0.001	Δμ = 0.38% t = 1.271 p = 0.204	Δμ = -5399 t = -4.601 p < 0.001	Δμ = -5326 t = -1.108 p = 0.268	Δμ = 1.69% t = 2.521 p = 0.012
Block Group (N = 1,104)	Number of Sites	r = -0.211 r^2 = 0.045 p < 0.001	r = -0.163 r^2 = 0.027 p < 0.001	r = 0.139 r^2 = 0.019 p < 0.001	r = -0.176 r^2 = 0.031 p < 0.001	r = -0.122 r^2 = 0.015 p < 0.001	r = 0.148 r^2 = 0.022 p < 0.001

RESULTS

Unit-hazard coincidence methods seem to suggest that there is little concern with environmental injustice in the Wasatch Front (see Table 2). Testing whether block groups with hazard sites differed with regard to disadvantaged populations from those without sites showed minimal differences. Of 1,104 census blocks groups, 683 (61.9%) had at least one hazard site. While differences in most categories were statistically significant, they were not large enough to be particularly meaningful. The mean non-White population percentage of block groups with at least one site was 16.7%, only 2.7 percentage points above that for those with no sites. Such a story is typical of most measures of disadvantaged socioeconomic status used in this study. A weakness of this method is that it treats as equal block groups with a single site and block groups with many sites. Given that block groups that had at least one site averaged 7.76 sites, and that 5% of block groups had 10 or more sites, this is an unrealistic comparison. But correlation of the number of sites with the demographic characteristics of block groups showed similarly weak findings, with correlations between the number of sites and percentage of disadvantaged populations all significant at $p < 0.001$ but with absolute values of coefficients less than 0.220. As 88% of

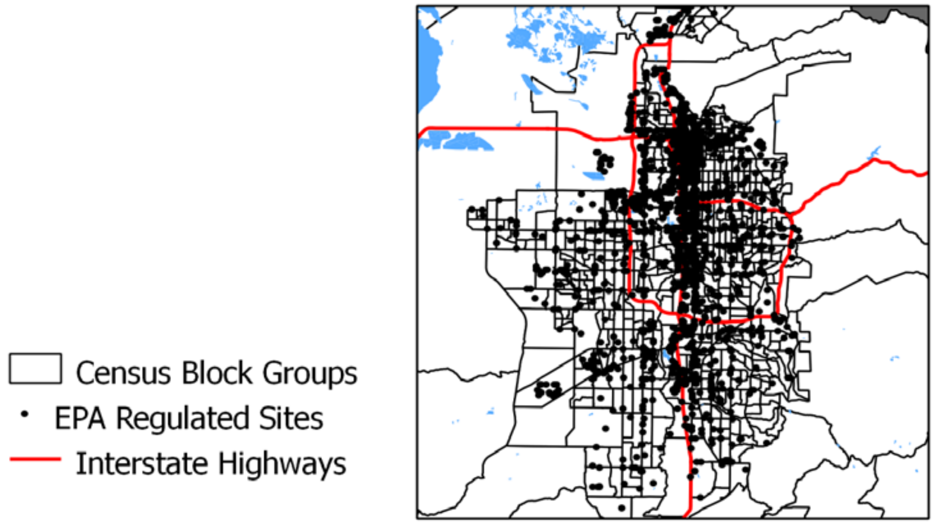

Figure 3: Coincidence of Hazard Sites and Census Block Group Boundaries in Central Salt Lake County

the block groups had no rural population, it was not considered necessary to repeat the tests using only urban areas.

Simple unit-hazard coincidence is a very poor measure of disparities in the Wasatch Front, however. The problem that Mohai and Saha (2007) noted regarding the proximity of sites to geographic unit boundaries is clearly present in the region. As the example of central Salt Lake County in Figure 3 illustrates, many sites are very near the boundaries of census blocks groups and thus affect more than just the single population of that block group. Thirteen percent of hazard sites are within 500m of the centroid of at least one census block group other than its own and 73% are within 1km of an adjacent group centroid; 21% are within 1km of at least 5 other group centroids. This suggests that unit-hazard coincidence does, indeed, greatly underestimate the populations affected by the hazards, and that a proximity measure is very much appropriate to the geography of the Wasatch Front.

Measuring environmental inequities using single-site proximity measures nonetheless suggests more substantial but still unremarkable environmental disparities (see Table 3). The mean distance to the nearest site of sites in block groups that had above average non-White populations was 972m ±92m, where the that of block groups with below average non-White populations was 608m ±39m ($p < 0.001$).

Table 3: Single-site Proximity

Population	Hazard	Race, Language, and Citizenship Non-White	Latino	Non-English-speaking	Linguistically Isolated	Non-citizen	Foreign-born
Random Points (N = 719)	Distance to Nearest Site	$r = -0.276$ $r^2 = 0.076$ $p < 0.001$	$r = -0.258$ $r^2 = 0.067$ $p < 0.001$	$r = -0.226$ $r^2 = 0.051$ $p < 0.001$	$r = -0.241$ $r^2 = 0.058$ $p < 0.001$	$r = -0.288$ $r^2 = 0.083$ $p < 0.001$	$r = -0.324$ $r^2 = 0.105$ $p < 0.001$
1km vs. 5km Centroid Containment	Individual Sites (N = 2,749)	$\Delta\mu = 7.1\%$ $t = 26.568$ $p < 0.001$	$\Delta\mu = 5.72\%$ $t = 25.057$ $p < 0.001$	$\Delta\mu = 2.86\%$ $t = 22.18$ $p < 0.001$	$\Delta\mu = 2.33\%$ $t = 24.086$ $p < 0.001$	$\Delta\mu = 3.07\%$ $t = 22.361$ $p < 0.001$	$\Delta\mu = 3.39\%$ $t = 22.292$ $p < 0.001$

Population	Hazard	Education and Income High School Graduate	College Graduate	Unemployed	Median Household	Per Capita	Poverty Level
Random Points (N = 719)	Distance to Nearest Site	$r = 0.171$ $r^2 = 0.029$ $p < 0.001$	$r = 0$ $r^2 = 0$ $p < 0.001$	$r = -0.118$ $r^2 = 0.014$ $p < 0.001$	$r = 0.285$ $r^2 = 0.081$ $p < 0.001$	$r = 0.095$ $r^2 = 0.009$ $p < 0.001$	$r = -0.322$ $r^2 = 0.104$ $p < 0.001$
1km vs. 5km Centroid Containment	Individual Sites (N = 2,749)	$\Delta\mu = -6.3\%$ $t = -28.894$ $p < 0.001$	$\Delta\mu = -7.77\%$ $t = -34.169$ $p < 0.001$	$\Delta\mu = 1.94\%$ $t = 19.576$ $p < 0.001$	$\Delta\mu = -4992$ $t = -31.347$ $p < 0.001$	$\Delta\mu = -3167$ $t = -33.213$ $p < 0.001$	$\Delta\mu = 5.31\%$ $t = 24.599$ $p < 0.001$

All correlation coefficients were significant at $p < 0.001$ and generally more substantial than those for unit-hazard coincidence, but only foreign-born population percentage and percentage below the poverty level rose to $|r| > 0.300$. Comparing the demographics of census block groups whose centroid falls within 1km of each hazard site with those falling within a 4km to 6 km ring around the site using a paired t-test also showed noticeable but not dramatic differences that are strongly significant statistical-ly. The mean difference in population percentages is quite substantial for non-White population (7.1 percentage points), Latino population percentage (5.7 points), and percentage below poverty (5.3 points). (High raw differences in education categories presumably reflect the much higher percentages of populations in those categories rather than major differences in outcomes.)

As discussed above, the site-based centroid containment method cannot account for the density of sites and thus the effects that multiple sites might have on the same population. Using populations as the unit of analysis with proximity-based measures of aggregate site effects does show strong disparities in environmental burdens (see Table 4), as can be examined visually in Figure 4. The mean number of sites within 1km of the centroid of block groups with above average non-White populations (>16.3%) was 13.9 ±1.6; among those with below average non-White populations the mean was only 5.2 ±0.5, *p*

Table 4: Population-based Site Density

Population	Hazard	Race, Language, and Citizenship					
		Non-White	Latino	Non-English-speaking	Linguistically Isolated	Non-citizen	Foreign-born
Urban Block Group Centroids (N = 987)	Number of Sites within 1km	r = 0.473 r^2 = 0.224 p < 0.001	r = 0.438 r^2 = 0.192 p < 0.001	r = 0.421 r^2 = 0.177 p < 0.001	r = 0.473 r^2 = 0.224 p < 0.001	r = 0.454 r^2 = 0.206 p < 0.001	r = 0.464 r^2 = 0.215 p < 0.001
Urban Block Group Centroids (N = 987)	Number of Sites within 3km	r = 0.539 r^2 = 0.291 p < 0.001	r = 0.475 r^2 = 0.226 p < 0.001	r = 0.435 r^2 = 0.189 p < 0.001	r = 0.507 r^2 = 0.257 p < 0.001	r = 0.521 r^2 = 0.271 p < 0.001	r = 0.55 r^2 = 0.303 p < 0.001
Random Points (N = 719)	Number of Sites within 1km	r = 0.552 r^2 = 0.305 p < 0.001	r = 0.542 r^2 = 0.294 p < 0.001	r = 0.459 r^2 = 0.211 p < 0.001	r = 0.535 r^2 = 0.286 p < 0.001	r = 0.49 r^2 = 0.24 p < 0.001	r = 0.493 r^2 = 0.243 p < 0.001
Random Points (N = 719)	Number of Sites within 3km	r = 0.636 r^2 = 0.404 p < 0.001	r = 0.592 r^2 = 0.35 p < 0.001	r = 0.5 r^2 = 0.25 p < 0.001	r = 0.572 r^2 = 0.327 p < 0.001	r = 0.556 r^2 = 0.309 p < 0.001	r = 0.578 r^2 = 0.334 p < 0.001

Population	Hazard	Education and Income					
		High School Graduate	College Graduate	Unemployed	Median Household	Per Capita	Poverty level
Urban Block Group Centroids (N = 987)	Number of Sites within 1km	r = -0.421 r^2 = 0.177 p < 0.001	r = -0.214 r^2 = 0.046 p < 0.001	r = 0.241 r^2 = 0.058 p < 0.001	r = -0.464 r^2 = 0.215 p < 0.001	r = -0.196 r^2 = 0.038 p < 0.001	r = 0.422 r^2 = 0.178 p < 0.001
Urban Block Group Centroids (N = 987)	Number of Sites within 3km	r = -0.428 r^2 = 0.183 p < 0.001	r = -0.156 r^2 = 0.024 p < 0.001	r = 0.194 r^2 = 0.038 p < 0.001	r = -0.474 r^2 = 0.225 p < 0.001	r = -0.139 r^2 = 0.019 p < 0.001	r = 0.396 r^2 = 0.157 p < 0.001
Random Points (N = 719)	Number of Sites within 1km	r = -0.509 r^2 = 0.259 p < 0.001	r = -0.268 r^2 = 0.072 p < 0.001	r = 0.313 r^2 = 0.098 p < 0.001	r = -0.459 r^2 = 0.211 p < 0.001	r = -0.219 r^2 = 0.048 p < 0.001	r = 0.526 r^2 = 0.277 p < 0.001
Random Points (N = 719)	Number of Sites within 3km	r = -0.557 r^2 = 0.31 p < 0.001	r = -0.282 r^2 = 0.08 p < 0.001	r = 0.328 r^2 = 0.108 p < 0.001	r = -0.486 r^2 = 0.236 p < 0.001	r = -0.211 r^2 = 0.045 p < 0.001	r = 0.516 r^2 = 0.266 p < 0.001

<0.001. At 3km, the mean for above average non-White population was 115.2 ±10.5 and 49.0 ±3.6 for below average populations. The number of sites within 3km of block group centroids correlates moderately to strongly (0.396 ≤ $|r|$ ≤ 0.550, p < 0.001 in all cases), with the percentage of the block group population in most disadvantaged groups. Correlations are more moderate (0.421 ≤ $|r|$ ≤ 0.473, significant at p < 0.001 in all cases) at 1km. Noteworthy exceptions in both cases are the percentage of college graduates, unemployment, and per capita income, which showed similarly significant but weak correlations.

Using random points produced results that are consistent with but slightly stronger than the block group centroids. Mean number of sites within 1km was 12.2 ±2.1 above average non-White populations and 3.6 ±0.5 among below average non-White populations; at 3km the mean was 108.3

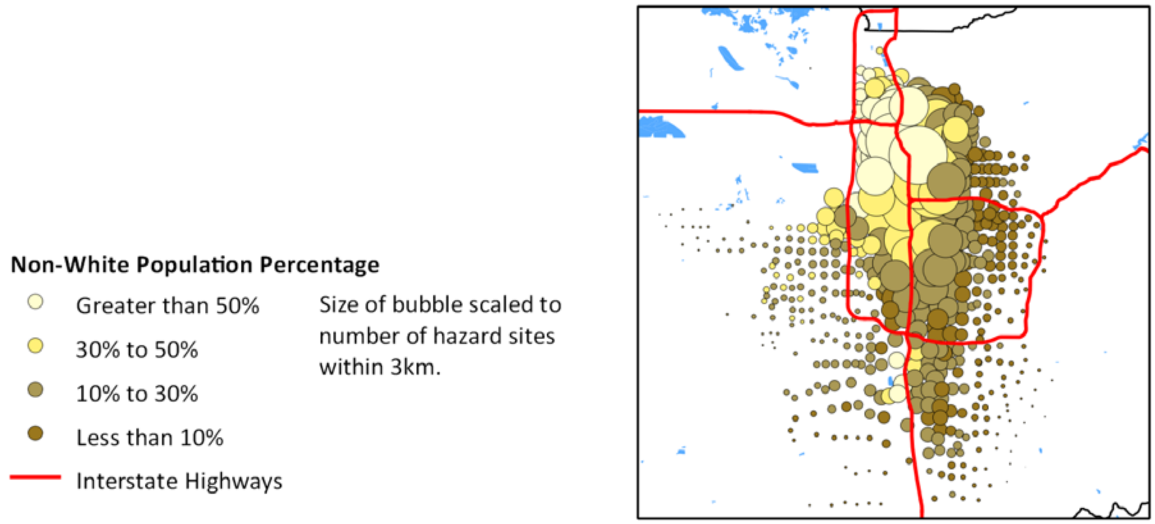

Figure 4: Census Block Groups by Non-White Population and Number of Hazard Sites in the Salt Lake City Urban Area

±13.9 and 36.8 ±3.3, respectively. Correlation was exceptionally strong with non-White populations (r = 0.636 at 3km) but at or above $|r|$ = 0.5 for all population measures except college graduate percentage, unemployment, median household income, and per capita income. The most noteworthy difference between the use of block group centroids and random points was that the latter show modest correlations between the number of sites and unemployment (r = 0.313 at 1km, r = 0.328 at 3km) that were not interesting at all in the case of the former. In all cases, findings were significant at $p < 0.001$.

A simple site count within a given distance accounts for the density of hazards but does not account for the differences in distance within the study radius. The Site Exposure Index does this, but shows that there is little difference in the relative distances of sites across study radii in this case (see Table 5). One should expect a strong correlation between number of sites within study radii and SEI, but a near perfect correlation would suggest that there are only minimal differences in the distribution of hazard sites within the 3km radii that need not be taken into account in analysis. Correlation coefficients are very similar to simple density measures, with correlation with the block group site count of r = 0.847 at 1km and r = 0.982 at 3km. The density of sites within 3km of the study point explains virtually all of the variation in the SEI, which suggests minimal variation in the distribution of sites within study areas.

Table 5: Site Exposure Index Disparity Measures

Population	Hazard	Race, Language, and Citizenship Non-White	Latino	Non-English-speaking	Linguistically Isolated	Non-citizen	Foreign-born
Urban Block Group Centroids (N = 986)	Site Exposure Index	r = 0.554 r^2 = 0.307 p < 0.001	r = 0.497 r^2 = 0.247 p < 0.001	r = 0.455 r^2 = 0.207 p < 0.001	r = 0.523 r^2 = 0.274 p < 0.001	r = 0.532 r^2 = 0.283 p < 0.001	r = 0.557 r^2 = 0.31 p < 0.001
Random Points (N = 701)	Site Exposure Index	r = 0.608 r^2 = 0.37 p < 0.001	r = 0.58 r^2 = 0.336 p < 0.001	r = 0.496 r^2 = 0.246 p < 0.001	r = 0.567 r^2 = 0.321 p < 0.001	r = 0.547 r^2 = 0.299 p < 0.001	r = 0.559 r^2 = 0.312 p < 0.001

Population	Hazard	Education and Income High School Graduate	College Graduate	Unemployed	Median Household	Per Capita	Poverty level
Urban Block Group Centroids (N = 986)	Site Exposure Index	r = -0.454 r^2 = 0.206 p < 0.001	r = -0.183 r^2 = 0.033 p < 0.001	r = 0.219 r^2 = 0.048 p < 0.001	r = -0.496 r^2 = 0.246 p < 0.001	r = -0.165 r^2 = 0.027 p < 0.001	r = 0.423 r^2 = 0.179 p < 0.001
Random Points (N = 701)	Site Exposure Index	r = -0.542 r^2 = 0.294 p < 0.001	r = -0.267 r^2 = 0.071 p < 0.001	r = 0.327 r^2 = 0.107 p < 0.001	r = -0.486 r^2 = 0.236 p < 0.001	r = -0.204 r^2 = 0.042 p < 0.001	r = 0.514 r^2 = 0.264 p < 0.001

As would be expected from this, the SEI shows roughly the same sensitivity to disparities in environmental burdens both for block group centroids and random study points.

The final step in the analysis was modeling the different factors. Stepwise ordinary least-squares regression was used to develop a model predicting the number of hazard sites within 3km of the random study points. In addition to the variables previously described two interaction variables, between median household income and non-white population percentage and between per capital income and non-White population percentage, were included based on the conjecture that income inequalities would be amplified by racial disparities. The resulting model showed eight variables as statistically significant predictors, five of which explained at least one percent of variance in the dependent variable. The preliminary model explains more than half of the variance (adjusted R^2 = 0.540), with most coming from the non-White population percentage (β = 1.297, adjusted r^2 = 0.403, p < 0.001).

The effects of the non-White population percentage is somewhat offset by Latino population percentage, however (β = -0.842), suggesting that the effects of race may be strongest for other non-White Groups. Repeating the stepwise regression model with the inclusion of the percentage of the population that is neither White nor Latino does not change the model's predictive power (adjusted R^2 =

Table 6: Stepwise OLS Regression Models

	All Study Points			Low Race Effect			High Race Effect		
Model Summaries	**Adj. R^2**	**F (d.f.)**	**p**	**Adj. R^2**	**F (d.f.)**	**p**	**Adj. R^2**	**F (d.f.)**	**p**
	0.540	106.414 (710)	< 0.001	0.496	92.054 (641)	< 0.001	0.779	49.73 (64)	< 0.001
Coefficients	**β**	**t**	**p**	**β**	**t**	**p**	**β**	**t**	**p**
Race									
Non-White	0.224	2.321	0.021	0.426	4.355	< 0.001	2.299	9.673	< 0.001
Latino by Non-White Interaction		Not Significant			Not Significant		-1.077	-5.282	< 0.001
Neither White nor Latino	0.331	6.979	< 0.001		Not Significant			Not Significant	
Income									
Per Capita Income		Not Significant			Not Significant		0.24	2.794	0.007
Below Poverty Level		Not Significant		0.114	2.489	0.013		Not Significant	
Unemployed	-0.086	-2.671	0.008		Not Significant			Not Significant	
Race × Income									
Median Household Income × Non-White	-0.789	-11.836	< 0.001	-0.551	-6.593	< 0.001		Not Significant	
Per Capita Income × Non-White	0.62	8.663	< 0.001	0.539	6.561	< 0.001		Not Significant	
Other									
Foreign-born		Not Significant		0.383	3.057	0.002	-0.93	-3.007	0.004
Non-citizen		Not Significant		-0.269	-2.178	0.03	0.606	2.015	0.048
Linguistically Isolated	0.193	4.101	< 0.001		Not Significant			Not Significant	
High School Graduate	-0.201	-4.391	< 0.001		Not Significant			Not Significant	
Population Density	0.075	2.792	0.005	0.166	5.565	< 0.001		Not Significant	

Latino population percentage, median household income, non-English-speaking population percentage, and college graduate population percentage were not statistically significant in any models.

0.540, exactly as before, though statistical significance improves from $p = 0.008$ to $p < 0.001$). But β is positive for neither White nor Latino population percentage (β = 0.331) rather than negative for Latino population percentage, and its inclusion both leads to the exclusion of Latino population percentage and drastically reduces β for the non-White population percentage (β = 0.224). Unemployment was the only statistically significant income variable and had little effect (β = -0.086, $\Delta r^2 = 0.005$). But the income-race interaction variables were notable predictors, though in opposite directions: β = 0.620 for per capita income interaction and β = -0.789 for median household income interaction. The final model is shown in Table 6.

While the overall model proved interesting, a scatterplot of study points by number of hazard sites within 3km and non-White population percentage revealed that there are, in fact, two separate groups of sites with very different effects profiles (see Figure 5). One subgroup of 70 sites showed both a

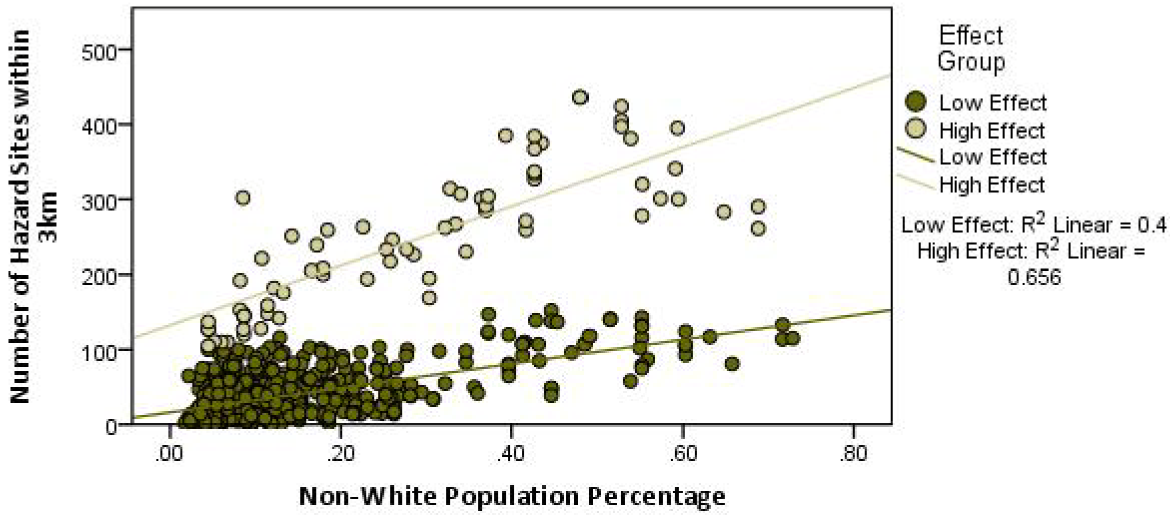

Figure 5: Study Points by Non-White Population Percentage and Number of Sites within 3km, Showing High and Low Race Effect Groups

greater number of sites in relation to non-White population overall and much sharper increases in number of hazard sites with increases in non-White population. In this group with high race effects, five variables were statistically significant at $p \leq 0.05$ in a stepwise linear regression. The regression model was exceptionally powerful for this group, with adjusted $R^2 = 0.779$ and statistically significant at $p = 0.048$.

In the low race effects group model, seven variables were significant at $p \leq 0.05$, and the regression model was somewhat less powerful than the high effects group but still substantial (adjusted $R^2 = 0.496$, significant at $p < 0.001$). In this model, per capita income directly (rather than in interaction with race) is a significant predictor, and median household income plays no role. In the low effects model foreign-born population percentage (β = 0.383, p = 0,013) and non-citizen population percentage (β = -0.269, $p = 0.030$) take on predictive roles not otherwise seen in the models. Income interactions with race continue to have opposite effects but of slightly smaller magnitude than in the model of all study points. Consideration of explanations for the differences between the two groups is presented below. Both models are also shown in Table 6.

DISCUSSION

The central goals of this study were twofold: to evaluate environmental disparities across the Wasatch Front region, and to introduce additional methodological techniques that may prove more useful in evaluating such disparities than those currently in common use. The findings with regard to the former are unequivocial: there are very substantial disparities in the burdens of environmental hazards across the Wasatch Front in which race is the key factor, independent of income. Mean non-White population percentages are higher in areas near hazard sites than further afield, and the nearest site to a non-White person is, on average, nearly 400m closer than to a White person. The correlation of non-White population percentage with the number of nearby sites is exceptionally high. Only the deeply flawed unit-hazard coincidence method suggests that there are no major disparities.

Moreover, income is generally a factor only when interacting with race. No income variable was statistically significant for more than one model, and β was generally much lower than other variables. Both variables measuring race-income interaction were statistically and practically significant to two of the three models. This challenges market dynamics explanations for disparities. Some scholars argue, as an alternative to race-based explanations, that either the operators of hazardous sites choose less expensive properties nearer poorer residential neighborhoods for purely financial reasons or that the siting of hazardous sites near a residential neighborhood depresses property values, leading to a in-migration by poorer residents. In either case, lower incomes and disproportionate poverty rates among minorities may create the appearance of racial injustice when race is, in fact, epiphenomenal. (Been, 1994) Market dynamics explanations should result in models that depend much more strongly on income and have little place for race except as a correlate of class. The primacy of race and the relative unimportance of income make this view untenable, a finding that is consistent with other studies of this potential explanation (Pastor, Sadd, & Hipp, 2001; Morello-Frosch, Pastor, Jr., Porras, & Sadd, 2002; Crowder & Downey, 2008).

This study proposed three methodological improvements over the existing literature. Consideration of site density proved quite effective in identifying environmental disparities. Weak relationships between populations and single sites became exceptionally strong when considering the number of sites that affect a single population. With an average of more than six hazard sites within 1km and nearly 58 within 3km of the study points, it is clear that most populations—disadvantaged or otherwise—are being affected by multiple sites, and an effective method of measuring inequalities must account for this. The difference in sensitivity to environmental disparities of the multiple-site and single-site measures reflects the underlying geography of urban environmental hazards much more fully than measures that do not consider the density of sites. The same cannot be said, however, for the other two methodological innovations. While the use of random points and the SEI did present important conceptual refinements, the effects in question (biases in census unit boundaries and in distribution of sites within study areas) proved to have insufficient influence on environmental disparities to justify the additional effort, at least generally.

Common to all three innovations, as well as others in the more recent generation of research in environmental injustice, is their reliance on GIS software. The sole virtue of the unit-hazard coincidence method is that it does not require the use of GIS; census unit demographics and the host units of sites are readily available and can be analyzed using methods widely used in the social sciences. Even identifying adjacent census units without GIS becomes an exceptionally labor-intensive task, and to manually locate and measure distances to sites becomes rapidly exhausting for even the most motivated of graduate assistants. Calculating the 3km SEI, for instance, required measuring the distances to more than 287,000 sites. But this study has shown conclusively the inadequacy of unit-hazard coincidence in the face of GIS assisted techniques: stark disparities were identified using GIS-based methods that were invisible to unit-hazard coincidence. Given that Quantum GIS, the software used in this analysis, is available as a free, open-source package suitable for most desktop computers and operating systems and the commercial ArcGIS package published by ESRI is comparable in its demands on financial and computing resources to common statistical packages, the lack of GIS is no longer a constraint that can justify the inadequacies of unit-hazard coincidence that this paper has demonstrated.

As always, answering one set of questions has posed others. The distinct relationships between race and site density of the high race effect and low race effect groups points to an additional hypothesis regarding the cause of environmental disparities. Mapping the two groups shows strikingly that all of the high effect study points are located within the Interstate-215 loop in Salt Lake County and an associated corridor along State Route 201. This area is one of the most substantial industrial corridors in the state, and also has its highest urban minority population concentrations. Comparing the site density per square kilometer and the non-White population percentage shows that both decrease steadily moving away from Interstate-15, which is the central artery of the industrial corridor. While not specifically tested in this study, the differences between the two race effects groups suggests the possibility that a threshold combination of minority population and industrial development could substantially increase the potential for environmental inequalities. Below such a critical mass there may not be sufficient industrial development to present elevated environmental burdens or sufficiently large concentrations of minority populations to disproportionately affect.

The relationship between Latino population percentage and hazard measures requires further explanation as well. Before considering the neither White nor Latino population, Latino population percentage mitigated the effects non-White population percentage on hazard density in all study points but added to those effects in interaction with overall non-White in high race effects areas. A potential explanation for this balances increased empowerment from overall population size against the ability to identify an area as distinct and identifiable racial community. As population proportion increases generally, a population is able to mobilize members outside of areas of immediate concern as allies in political battles and increase their political efficacy as, for example, homosexuals in states that allow gay marriage or civil unions have done in the fight against gay marriage bans in other states. But when a politically disadvantaged group becomes sufficiently concentrated to be a geographically identifiable community, association of the area with the group among those with attitudes detrimental to that community's interests—for example, overt racism or a sense that the community poses little political threat—may find themselves with an object toward which to direct those attitudes that is not present in more diffuse communities. Under such circumstances, the concentrated Latino community in Salt Lake City might be able to prevent injustices elsewhere in the state while at the same time becoming a target of injustices themselves. Such a hypothesis is, of course, purely conjecture at this point but is sufficiently plausible to merit further investigation.

A final relationship remains more fundamentally remain puzzling. The coefficients of regression for the interaction of non-White population with the two income variables are in opposite directions, median household income being negative while per capita income being positive. Median household income by itself was also a stronger correlate of most measures of hazard than per capita income. It is not clear why the differences between the two should be so substantial. Plausible explanations include relationships between labor force participation, employment, number of children, or number of family members working and race that would lead to different patterns of income in relation to households and individuals, but no further work on this question was pursued for this paper.

This study is limited by several factors. It is, first and foremost, a regional study. While its methods are unquestionably generalizable, its conclusions are not; relationships between demographics and environmental hazards present in this study may not be present in others. This is one of the major criticisms that Bowan and Wells (2002) offer. A study of environmental injustice in any one region does not establish with any degree of reliability the existence of it as a nation-wide concern that one might think justifies the attention of federal policymakers such as President Clinton's Executive Order 12898 or considering environmental burdens under civil rights laws. This reasoning, however, is simplistic. The absence of consistent environmental injustices on a national scale no more precludes concern with regional injustices than the absence of formal segregation nationally precluded concern with areas where it was prevalent. Scholars in environmental justice must be sensitive to regional and local differences in environmental inequalities, and explaining such differences is a potentially fruitful but so far unexplored line of inquiry.

This study also suffers from weaker validity in comparison with risk or exposure models. The latter are, unquestionably, more effective measures of environmental burdens than mere proximity to sites. They are also the only tool that has validity at the level of neighborhoods or specific sites. Those concerned with whether a specific project poses concerns to a specific community (for example, in the context of an Environmental Impact Statement) are best advised to pursue the more rigorous and—more to the point—more fine-grained approach. The methods used here are best suited for larger geographic areas where it can be assumed that local conditions at any one site are balanced by other sites. In trying to identify why some regions present more serious problems than others, the additional methodological complexity of risk or exposure modeling may not be necessary.

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