

PATTERNS OF HAZARDOUS WASTE IN THE UNITED STATES: ANALYZING
RURAL ENVIRONMENTAL JUSTICE WITH SPATIAL DATA

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Abstract

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This thesis uses spatial data to test environmental justice theories concerning how race and class determine proximity to hazardous waste in the rural United States. Environmental justice studies to-date are dominated by urban focused projects working at tract, city and county levels of analysis. This study joins a growing body of literature calling for and demonstrating the methodological improvements of spatial data analysis using Geographic Information Systems technology. Spatial data analysis enables measurement of actual hazardous wastes to neighboring populations, as opposed to assuming residents of a certain census tract or county are equally exposed to an environmental burden. Using logistic regression, I assess the degree to which Hispanic, African American, Native American and lower class populations reside in disproportionate proximity to hazardous waste in rural regions. Findings indicate that rural places with a baseline level of economic activity and higher proportions of African American and Hispanic residents are significant predictors of hazardous waste.

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CHAPTER ONE: INTRODUCTION

Increasingly sophisticated spatial analyses of hazardous waste distribution in the United States strengthens the position of environmental justice activists, showing that it is the less affluent and often non-white who work and reside in closest proximity to environmental pollutants (Downey 2003; Mohai and Saha 2007; Hooks and Smith 2004; Smith 2007). The term “environmental justice” emerged in the 1980s to describe situations in which certain groups bear disproportionate environmental burden (Bryant and Mohai 1992; Bullard 1993; Mohai and Saha 2007). Such environmental burdens range from poor air quality to polluted waterways, and are increasingly connected to plant, animal and human health problems (Carson 1962; Davis 2007). Environmental justice can further be understood as a physical reinforcement of social inequality, raising pivotal questions about the significance of race and class in the United States today. Indeed, environmental justice analyses have begun to contribute to wider academic debates. Specifically debates concerning the degree to which race and/or class structure current inequality and the distribution of social “goods” and “bads.”

The environmental justice movement gained momentum with the 1987 report of the United Church of Christ Commission for Racial Justice, *Toxic Waste and Race in the United States*, finding that on a national level people of color face unequal exposure to toxic waste (United Church of Christ 1987). In 1994, as an indicator of the movement’s building influence, President Clinton signed an environmental justice executive order, mandating all Federal agencies to be cognizant of the environmental impacts of their programs and policies on low-income minority populations, and to work towards achieving environmental equity (United Church of Christ 2007). Therefore, continued

empirical research on environmental injustices is necessary to inform public policies seeking to ameliorate this situation, while also informing social movements and injured parties.

Theoretical Context

Within the field of sociology, scholars argue that environmental inequality results from race, class and power inequalities, often in the capitalist context - with varying degrees of importance attributed to each system (Smith 2007; Downey 2003; Wilson 1987; Massey and Denton 1993; Pellow 2002). This thesis places race and class environmental justice debates within the context of political-economic claims made by the “treadmill of production” theory. Schnaiberg and Gould’s (1994) treadmill of production theory posits that environmental degradation and social inequality are the structural foundation for *and* outcome of growing capital. The authors argue that the continued re-investment of profits into the production of goods (namely through new technologies) exacerbates environmental withdrawals and deposits, while further isolating wealth in the hands of an international power elite. Treadmill theorists argue that it is the least powerful members of society who bear the brunt of environmental wastes, both in the workplace and via residential proximity to pollutants (Gould, Schnaiberg and Weinberg 1996). As the treadmill theory predicts, physical environmental injustice has been found in both quantitative and qualitative studies. However, there are few studies to-date that have specifically examined environmental inequality in the rural United States. Therefore, the main theoretical thrust of this thesis is testing the applicability of environmental justice hypotheses in non-urban regions.

Methodological Aspects

The majority of environmental justice quantitative analyses use site proximity assessments, which entail studying the characteristics of populations within a given distance from an environmental burden (Mohai and Saha 2007). This method operates under the assumption that proximity to a polluting source entails negative exposure. Most environmental justice proximity studies use what Mohai and Saha (2006) call “unit-hazard coincidence” methods, where a given unit (such as U.S. county or census tract) is used, the number of hazardous sites summed, and census demographics at the chosen unit are assessed. In contrast to the “unit-hazard coincidence” approach, are the newer “distance-based” approaches, advocated by Mohai and Saha (2006, 2007) and Downey (2003), which pertain to Geographic Information System (hereafter GIS) based methods. Here actual proximity to hazardous waste sites can be measured and analyzed. This means that instead of being limited to county-level findings, analyses of proximity to environmental burden can be done spatially through digital GIS mapping at any scale desired. For example, one can collect data in GIS on all towns with a hazardous waste site within 1 mile of their borders. Distance-based approaches provide superior assessments of proximity as compared to “unit-hazard” approaches, as units such as counties or census tracts do not have uniform sizes or shapes and additionally provide no information on the dispersion of communities within the given unit (Hooks et al. 2007; Mohai and Saha 2007).

Study Aims

This study contributes to the environmental justice literature in four key ways. First, I use GIS to analyze actual spatial relationships between populations and hazardous

waste, joining Downey (2003; 2006), Mohai and Saha (2006; 2007) in both calling for and demonstrating the superior analytical value of distance-based environmental justice assessment. Second, I expand the universe of hazardous waste facilities analyzed in comparable studies, an inclusion resulting in my hazardous waste data set capturing close to all regulated storage sites in the U.S. (Anderton et al. 1994; Been and Gupta 1997; Commission for Racial Justice 1987; Mohai and Saha 2007; Oakes, Anderton, and Anderson 1996). Third, the focus of my analyses are rural as opposed to urban regions, namely due to the predominant focus on urban environmental justice analyses in the literature and lack of deliberate rural environmental justice studies (Hooks and Smith 2004; Lichter, Parisi, Grice, Taquino 2007). Finally, I create a longitudinal data set of hazardous waste sites active between 1991 and 2003. Unfortunately I do not take advantage of the longitudinal dimension of this data set due to complications with data comparability between years (among other issues later discussed). Lessons learned in my attempt to capture growth and decline of hazardous waste (i.e. number and location of new waste sites in addition to the number and location of closed sites) are taken up in chapter six.

Research Questions

With this data in map form, environmental justice questions can be assessed using census “places” as the unit of analysis. “Places” are villages, towns, and cities recognized by their inhabitants, as opposed to census-structured areas such as counties or tracts, and are furthermore well-suited to rural spatial analysis (where county and tract size exhibit extreme variety) (Census 2005). In this paper I address the following questions: *1) Do Hispanic, African American or Native American populations live in*

disproportionate proximity to rural hazardous waste disposal facilities? 2) Are renters and persons living below poverty living in disproportionate proximity to rural hazardous waste disposal facilities? In addressing these questions, I will contribute to environmental justice debates by engaging in these dialogues with spatial evidence (Downey 2003; Been and Gupta 1997; Hooks and Smith 2004; Mohai and Saha 2007; UCC 1987, 2007).

Thesis Outline

Chapter two discusses the pertinent environmental justice research and theory this paper draws from and contributes to. I point out major theoretical/methodological debates surrounding the roles of race and class in the distribution of social ‘bads’ – here hazardous waste facilities. In chapter three I provide information on project data and methodology, explaining dataset construction using U.S. hazardous waste sites, and data on rural population centers geocoded with GIS technology. Additionally in this chapter I present my specific research questions. Chapter four presents a replication of previous environmental justice models, comparing logistic regression outcomes for two different U.S. hazardous waste datasets. I then turn to extended data analysis in chapter five, where I run logistic regression models over varied distances and variable categorization methods, examining the effects of space and population thresholds in predicting hazardous waste presence. Finally, chapter six provides a discussion of results and suggestions for future research.

CHAPTER TWO: LITERATURE REVIEW AND THEORY

An overarching question posed by environmental justice research is: are low-income minorities unfairly exposed to pollution? Sociologists frequently address this question empirically using ‘site proximity assessment,’ an approach analyzing the relationship between hazardous sites and the populations who live near them. In the site proximity assessment literature researchers have found mixed results regarding whether low-income minority populations live closer to polluting facilities than others, as the scale and type of facilities used tend to vary. Within quantitative national-level environmental justice studies alone, researchers have compiled hazardous waste data from various Environmental Protection Agency (hereafter EPA) databases and commercial listings. Units of analysis additionally vary (zip code, county, tract), as well as sampled control groups, all of which make empirical assessment of environmental justice uniquely complex and controversial (UCC 1987; Anderton et al. 1994, see Lui 2001 for detailed discussion).

That said, most environmental justice research finds that racial and economic variables do significantly relate to polluting sites, with varying significance attributed to either race or class (Been 1995; Downey 2003; Hooks and Smith 2004; Lester, Allen, and Hill 2001; Rinquist 2005; Smith 2007). There is considerable debate surrounding whether race or socio-economic status drives disproportionate distributions of environmental burdens, when unequal distributions are found (Downey 2003; Mohai and Saha 2007; UCC 1987, 2007; Smith 2007). Empirical evidence has been gathered in

support of both race and class prominence arguments, however scholars have also noted that such debates are moot in light of the tight coupling of racial and class-based inequality (Downey 1998). Furthermore, a handful of studies have found neither race nor income to relate to locations of environmental “bads” (Anderton, Anderson, Oakes, and Fraser 1994; Davidson and Anderton 2000)¹. With respect to the varied empirical environmental justice findings, several authors show that units of analyses and control populations can significantly determine quantitative outcomes (Mohai 1995; Lui 2001). For the purposes of this paper, special attention will be paid to assessing the extent to which race and socio-economic variables at the place level, predict the spatial location of rural hazardous waste facilities nationally.

Race

Environmental justice literature suggests race is more highly correlated than class with the location of polluting facilities. This result has been found empirically across scales and methodologies (Bullard 1983; UCC 1987, 2007; Mohai and Bryant 1992; Mohai and Saha 2007; Pastor, Sadd, Hipp 2001). When discussing race in such a context, questions arise concerning the intentionality of siting polluting facilities in predominantly minority areas. Mohai and Saha (2007: 345) write, “Deliberate targeting of new facilities may occur because minority communities over time have come to be recognized as the ‘paths of least resistance’ by government and industry.” Race scholars argue that a wide range of mechanisms are responsible for the disproportionate environmental exposure and furthermore decreased life chances of non-whites. These include historic legacies of

¹ Anderton et al., (1994) has received scathing criticism from EJ researchers, primarily due to the study being funded by WMX Technologies, Inc. “the largest commercial handler of solid waste in the world” (Lui 2001: 243). Numerous methodological criticisms are detailed in Goldman and Fitton 1994; Mohai 1995; and Goldman 1996.

slavery, intergenerational transfer of wealth, racist policies such as “redlining” in financial investment, housing market segregation, employment segregation, and furthermore what Bonilla-Silva (1996) terms “racialized social systems.” Bonilla-Silva’s structural understanding of race, “refers to societies in which economic, political, social, and ideological levels are partially structured by the placement of actors in racial categories” (1996:469). A structural conception of race is particularly powerful as often, in the case of environmental justice debates, it may be difficult to find documented evidence of racial discrimination in government and industry siting decisions. Racial oppression continues today via so-called “color blind” policies, which paradoxically attempt to fix racism by ignoring its existence. This thesis contributes towards a structural understanding of race in the U.S. by assessing the empirical reality of decreased life-chances for non-whites at the most basic level of proximity to hazardous waste. I include Native American populations in my analyses of race in the U.S. given this study’s focus on environmental justice in rural regions and the notable dearth of environmental justice literature on Native American populations (LaDuke 1999; Hooks and Smith 2004).

Class

Closely tied to racial considerations, are those pertaining to economic factors in understanding the distribution of polluting facilities. One prominent argument is that new facilities locate in places where land and operation costs are low, therefore unequal exposure to facility pollutants is attributed to the correlation of low land costs, low-income housing and minority residence (Mohai and Saha 2007; Rhodes 2003). A second argument termed “minority move-in” posits that after a facility comes to a community,

land values may decrease followed by white-flight and an influx in non-white residents (Pastor, Sadd and Hipp 2001). In his longitudinal study of race, class and polluting facilities in Detroit, Downey (2003) finds that minority populations are more likely to work in or near environmental “bads.” However, these populations were also found to live further from these environmental burdens. Downey speculates that this finding for one Detroit region, may be due to housing segregation which, in some cases, happens to shield minorities from residing near point source air pollution. In a second spatial analysis of environmental justice in Detroit, Smith (2007) finds that low-income regions are stronger predictors of proximity to landfill and Superfund sites, as these environmental “bads” tend to be located near industrial areas on navigable waterways. Overall, these studies of single cities illustrate that specific regional and historical contexts provide improved insights into the actual mechanisms and processes that sustain environmental inequality. Indeed, (Smith 2005) argues that combining historical and longitudinal data provides the strongest insights into the causal relationships underlying environmental inequalities found today.

The Treadmill of Production

As mentioned in the introduction, environmental sociologists are increasingly interested in the ongoing production of environmental “bads” driven by the “treadmill of production,” and furthermore how these “bads” are distributed across race and class (Gould and Schnaiberg 1994). Schnaiberg (1980) and Gould and Schnaiberg (1994) argue that the treadmill of production’s incompatibility with ecological capacity leads to financially unaccounted for and excessive wastes. Under structures of U.S. race and class-based inequality, treadmill processes exacerbate and perpetuate disproportionate

environmental impact – by increasing raw material access for a powerful minority, and decreasing environmental access and health for a marginalized majority. The treadmill of production theory as discussed by Pellow (2002), contributes to shifting dialogues away from race vs. class in the environmental justice literature, and towards discussion of environmental inequality as a process. Again, increasing interest in longitudinal analyses and mixed-methods approaches invite increased opportunity for understanding the mechanisms that drive inequality.

Geographic Information Systems and Spatial Analyses

GIS technology is a uniquely useful tool for exploring spatial patterns of race, class and production in relation to environmental “bads”(Downey 2003, 2006; Mohai and Saha 2006). GIS can map both discrete and continuous variables (the former termed “vector” and latter “raster”), such as hazardous waste sites as points or hazardous waste leakage into ground water as a continuous index. On and around our unit of interest, it is possible to add additional variables of interest to the map by creating new “layers”(Chang 2008). With information on hazardous waste in one layer, a second layer containing information on block, tract, or place-level demographic data can be intersected, creating a new spatial data set. For example, in this project I intersect rural towns with hazardous waste sites falling within 0, 1, and 3 kilometers of each town’s boundary. As described later, this data set allows me to ask new questions about changing spatial environmental justice patterns that would not otherwise be possible without GIS (see Downey 2006 for extensive discussion of how GIS technology changes the types of questions we can ask as researchers).

Rural vs. Urban Environmental Justice

Finally, this project expands environmental justice analyses theoretically and methodologically by shifting the spatial focus from urban to rural areas. Urban environmental justice studies have been criticized for attributing disproportionate exposure to racism, rather than the clustering of commercial activities in large urban areas (Lui 2001). Such critics argue that concentration of low-income and non-white populations in urban areas is evidence of inequality in-and-of-itself (Lui 2001). By focusing analyses on rural areas, it is possible to assess hazardous wastes unique to rural areas in conjunction with their population demographics and economic characteristics. Furthermore, with the recent census inclusion of “place” as a unit of demographic assessment, this project follows Lichter et al.(2007) in using census place as the unit of analysis of rural spatial phenomena. The following chapters attempt to synthesize recent methodological innovations in spatial social science research, while testing the applicability of prominent environmental justice theories in non-urban regions.

CHAPTER THREE: DATA AND METHODS

Chapter Overview

This chapter details the construction of my data set using census ‘places,’ and hazardous waste disposal sites in GIS. To begin, I explain the logic behind building a census place-based dataset. Selection and explanation of independent variables is detailed in a discussion of census demographic data. Next, I describe the universe of hazardous waste sites from which I conduct later analyses, explaining how I construct my dependent variable. I then explain the process of attaching hazardous waste data to census data in a GIS map, and how intersecting these data sources enables the creation of a new spatial dataset. Finally, I present operationalized research questions.

Census Data for Place

Data from the U.S. Census provides information on the locations of “places” or population concentrations, and their economic and demographic characteristics for the entire country. Instead of areas defined by the census for statistical purposes (e.g., census blocks or tracts), I focus on “places” – geographically-bounded sites that are recognized by inhabitants. Primary emphasis is on incorporated towns and cities, but I also examine “census designated places” – i.e., “settled concentrations of population that are identifiable by name but are not legally incorporated under the laws of the state in which they are located” (U.S. Bureau of the Census 2005). I focus on places in order to bring the analysis closer to the lived experience of inhabitants. Data provided by the census allows for treatment of places as polygons, since information is available on the boundary

of each place. That is, vertices (measured by latitude/longitude coordinates) of the polygon demarcating the boundary are provided for each place (U.S. Bureau of the Census 2005; also see Figure 1 for a GIS snapshot of places).

There are 21,093 census places that existed in both 1990 and 2000 (Lichter 2007; U.S. Census Bureau 2007). I focus this study on rural environmental justice, as there is limited attention paid to the rural context in existing literature, and census “places” are not a suitable unit for analyzing urban demographics and waste (i.e. New York City would be one place). To access rural and isolated regions, I use a U.S. Department of Agriculture measure of “ruralness,” where counties are given a score of 1-9; 1 is high population density (urban) and 9 is low population density (rural). I excluded places in counties with a urban-rural score lower than 4 – allowing me to focus on counties with a total population of 250,000 or fewer². Of the 21,093 places in the United States in 2000, these restrictions reduced the sample to 12,369 places.

Race, Ethnicity and Class Characteristics of Places

Contributors to the environmental justice literature are concerned with uneven exposure to environmental toxins across race and class-based hierarchies. In the following analyses, 1990 census data are used to construct both continuous and categorical race and class measures. Continuous race measures include: percent Hispanic, percent Native American, and percent African-American. Continuous class measures include: percent renter and percent living below the poverty line. Control variables account for phenomena aside from race or class that might account for the presence or absence of hazardous waste in a rural community. These include: unemployment rate,

² The Rural-Urban continuum values are re-assigned each decade, for this study I use the 1993 rural-urban continuum values (U.S. Department of Agriculture).

percent of population with bachelor's degree or higher, percent employed in executive, administrative, and managerial jobs (white collar), percent employed in manufacturing occupations (blue collar), and percent employed in farming, fishing and forestry occupations. Building on social ecology understandings of the importance of regional processes, I include dummy variables for each census region (Hooks, Mosher, Rotolo and Labao 2004; Lichter et al. 2007).

Whereas continuous measures are used for analyses in chapter four, I define key environmental justice variables categorically to ease interpretation with log odds in extended analyses found in chapter five³. The key selected environmental justice variables are defined as follows: Hispanic populations of at least 10 percent or greater; African American populations of at least 10 percent or greater; Native American populations of at least 10 percent or greater; renter populations of 10 percent or greater; percent below poverty 10 percent or greater – where each variable is dichotomous and coded 1 if the condition is met, 0 if the condition is not met in a rural place. Descriptive statistics for the continuous data set are provided in chapter four, where I replicate Mohai and Saha's (2007) model. Descriptive statistics for the same data set with selected measures in categorical form is provided in chapter five.

Spatial Inequality and GIS

Space is the pivotal variable in environmental justice analyses, asking: how are physical wastes spatially distributed across communities? Recent work in the sociology of spatial inequality emphasizes patterns which social inequality takes across space,

³ Full model analyses were performed with key environmental justice variables in rate form, and this did not affect outcomes shown. Results from logistic regression in log odds can be interpreted in a straight forward manner. For example in table 5.2 the log odds value for places with 10% or more renters is 8.24 – this means that places with 10% or more renters are about 8 times more likely to contain hazardous waste than places with less than 10% renters.

termed the “society-in-place” approach (Lobao, Hooks, Tickamyer 2007). This perspective examines how spatial phenomena – here the interaction of waste and population – provide opportunities to examine “intersecting social relations” such as power and inequality (Lobao, Hooks, Tickamyer 2007; Massey 1994; Hudson 2001). Drawing on this “spatial-turn” in sociology, environmental justice research is beginning to use GIS methods to map actual relationships between facilities and their proximate communities (Mohai and Saha 2006, 2007; Downey 2003, 2006; Smith 2007). As described above, GIS methods provide improved techniques for site proximity assessment, enabling greater control and precision in understanding the conditions under which groups experience exposure to “environmental bads.”

Research comparing unit-hazard and distance-based approaches provide evidence that mixed results in environmental justice hazardous waste studies are in large part due to reliance on unit-hazard methods (Mohai and Saha 2007). To demonstrate the superiority of distance-based methods, Mohai and Saha (2007) examine the location of 608 facilities that store or dispose of toxic waste. On the methodological front, they provide evidence of the robustness of distance-based methods when compared to the standard approach. The authors:

Demonstrated that when racial and socioeconomic disparities around the nation's [toxic waste facilities] are analyzed by applying distance-based methods, such disparities are found to be greater than when the unit-hazard method is applied. Furthermore, distance-based methods lead to different assessments about the relative importance of racial and nonracial factors in the distribution of [toxic waste facilities] (Mohai and Saha 2007:396).

The methodological superiority of site-proximity GIS-based approaches is clear, again due to the unit-hazard methodology being limited to units (such as counties or census tracts) that do not have uniform sizes or shapes and additionally provide no information

on the dispersion of communities within the given unit (Hooks et al. 2007; Mohai and Saha 2007).

Hazardous Waste Sites Monitored by EPA

To capture hazardous waste sites, I follow previous studies by using government data on regulated waste storage locations (United Church of Christ 1987; Anderton et al., 1994; Been and Gupta 1997; Mohai and Saha 2007). Every two years, as dictated by the EPA's Resource Conservation and Recovery Act (RCRA), operating transfer, storage and disposal facilities (hereafter TSDf) are summarized in the *Biennial Reporting System* (hereafter BRS) (EPA National Biennial Hazardous Waste Report 1991-2003). This report provides information on facility location, activity, and toxic materials stored. In the 2001-2003 BRS there were 1,726 operating TSDfS in the United States managing 42 million tons of hazardous waste⁴. Since 1989 when the EPA first released the data on operating TSDfS, approximately 10,196 different sites have been identified. Beginning with the 1989 BRS report and continuing through 2003, raw data and coding materials are available on the EPA website⁵. To create a longitudinal dataset of active TSDfS by year, pertinent variables were extracted from BRS raw data enabling tracking new facilities and those that have closed during the study period⁶.

The individual BRS datasets from 1991 to 2003 present methodological challenges, regarding comparability between biennial reports. These include issues such as changing variable codes over reporting years, in addition to the creation of new

⁴ 2003. National Biennial Report. The BRS report additionally contains hazardous waste data for Large Quantity Generator facilities and Small Quantity Generator facilities. Hazardous waste cannot remain at these sites for longer than 90 days. Available on-line at:
<http://www.epa.gov/epaoswer/hazwaste/data/biennialreport/index.htm>

⁵ Though the EPA indicates that 2005 BRS data are complete and available, they do not provide on-line access at this time.

⁶ Extensive information on TSD facilities exists, that will be used in future research. For instance we can track and map facilities by storage method i.e. incineration, underground injection, landfill etc.

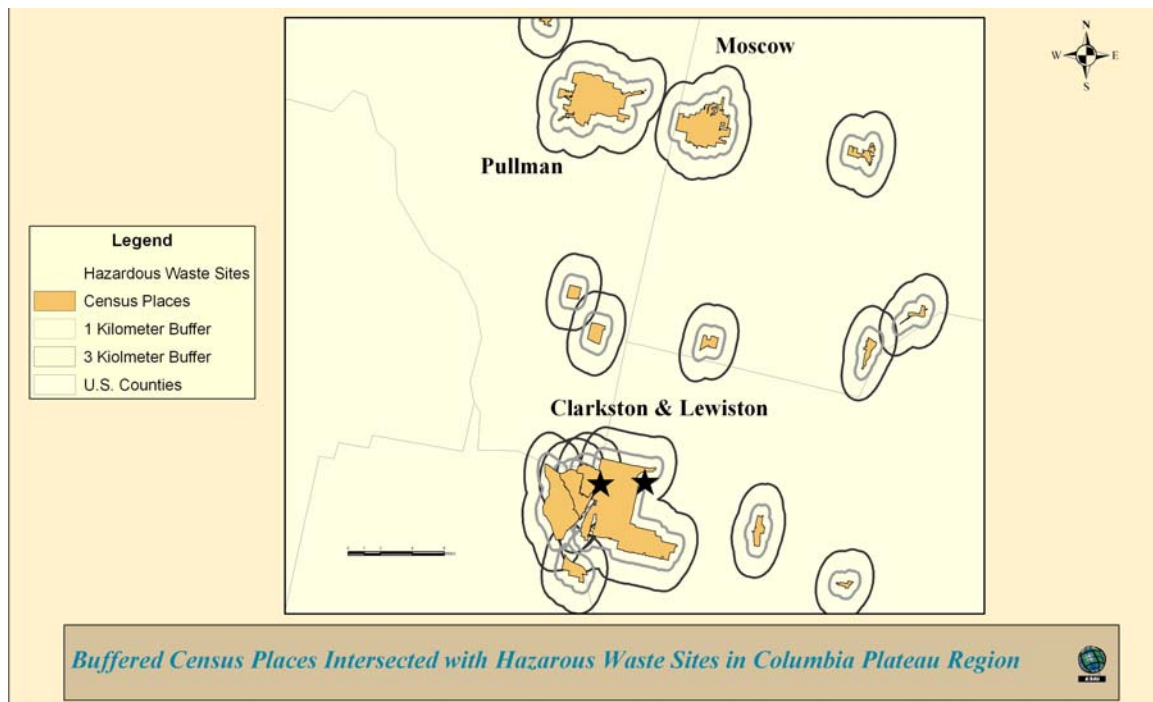
variables and dropping of previously used ones. Furthermore, definitions of what constitutes hazardous waste have changed over the past decade. Careful attention has been paid to where and when such changes occur through painstaking analysis of biennial reports and instruction manuals. The key change in RCRA requirements (for the purposes of this study) is the 1999 report excludes wastewater treatment of hazardous waste. The number of active TSDF sites in 1997 is 1,756 and the number of active TSDF sites in 1999 is 1,580. Given that I have not collected data on the type of waste treatment used at each site, I am not able to tell which sites from 1997 disappear in 1999 due to this definitional change. Though my main interest was to analyze the locations of new TSDF growth between 1991 and 2003, exploration of my longitudinal data set revealed a number of additional complications. Principally, the number of rural TSDFs is quite small compared to those found in urban regions (see Table 5.3). More importantly though, it is quite common for TSDFs to close and apparently re-open in later years. In order to overcome these obstacles, I sum all places with TSDFs present at any point between 1991 and 2003. Therefore my dependent variable, TSDF presence, is a dichotomous variable, 1 if the place buffer intersected a TSDF (at 0, 1 or 3 kilometers), and 0 if the place does not. Following Saha and Mohai (2007) and Been and Gupta (1997), I employ logistic regression to test the predictive power of demographic characteristics on TSDF presence.

TSDF Data in GIS

Over the past year, my colleagues Shushanik Makaryan, Ana Cavanaugh and I processed BRS data into GIS maps. This entailed first obtaining latitude and longitude coordinates from TSDF addresses provided by the BRS database. Addresses were taken

from all 10,196 TSDFs ever active between 1991 and 2003, and geo-coded to assign latitude and longitude coordinates to each address. Of the 10,196 TSDFs ever active, this project data set contains 7,504 successfully geocoded sites, representing facilities with verified geographic locations from BRS databases⁷. With latitude and longitude coordinates Shushanik Makaryan processed the TSDf sites in GIS, enabling us to create points on a U.S. map for each TSDf location. With this data in GIS, “buffers” were created around each census place from 2000. A buffer is an outline of a designated map feature (here a census place). Figure 1 provides a visual snapshot of the GIS buffering process, depicting buffered census places in the Columbia River plateau region.

Figure 1. GIS map intersecting buffered census places and TSDf sites (represented by stars).



⁷ The accuracy of reported facility locations varies, accordingly of the 10,196 total TSD sites, 7,504 were geocoded by address whereas remaining sites were geocoded to the facility zip code (these 2,692 imprecise sites are not included in data analyses).

These buffers were intersected with all TSDFs within selected distances (here 0, 1, and 3 kilometers) from the census place.

This paper builds on our previous research by attaching year data to each TSDF in the BRS 1991-2003 data set. I was able to use data on buffered census places (i.e. towns with 0, 1, and 3 kilometer outlines drawn around them), which had been intersected with TSD sites active from 1991 – 2003. Essentially, I merged the data on TSDF year(s) of operation with the GIS map of census places and TSDF location.

Research Questions

This paper addresses two research questions for rural U.S. regions. 1) Are places with higher concentrations of Hispanic, African American and Native American populations positively correlated with TSDF presence? 2) Are places with higher concentrations of renters (serving as measure of class here) and individuals living below poverty positively correlated with TSDF presence?

CHAPTER FOUR: REPLICATION OF PREVIOUS MODELS

Overview of Chapter Four

This chapter features a replication of the most recent national TSDf analysis employing GIS spatial data, Mohai and Saha's (2007) "Racial Inequality in the Distribution of Hazardous Waste: A National-Level Reassessment." This paper illustrates how environmental justice findings differ based on unit or distance-based methods, by replicating previous studies (using the same TSDf sample) and contrasting findings. Mohai and Saha (2007) find that unit-based analyses have underestimated the strength in which race predicts hazardous waste when compared to distance-based methods. In this chapter I replicate Mohai and Saha's logistic regression model in order to contrast two key issues. First, I am interested in the extent to which environmental justice variables predict hazardous waste presence in rural areas as opposed to urban ones. Secondly, my TSDf data captures facilities where hazardous waste is both produced and stored onsite, and facilities that receive waste from offsite (as discussed below, Mohai and Saha's TSDf universe captures only offsite waste receivers).

Comparison with Previous TSDf Spatial Analyses

I begin analyses by replicating Mohai and Saha's (2007) logistic regression model with my TSDf data set, noting what differences emerge when identical hypotheses, methods, and models are used on different TSDf populations (see Table 4.1 for descriptive statistics of variables used in this analysis). The universe of TSDf sites in this study differs with Mohai and Saha's (2007) in five principle ways. First, as discussed earlier, recent environmental justice studies by Been and Gupta (1997) and Mohai and Saha (2007) use a TSDf data set with 608 commercial (offsite receivers of

hazardous waste) sites. This universe was compiled from over three sources: Resource Conservation and Recovery Information System (RCRIS), the Environmental Services Directory, and other publicly available lists of storage facilities (Been and Gupta 1997). Been and Gupta's 608 TSDf universe was compiled from over three non-mutually exclusive data bases, that required that the researchers call each facility to confirm their address and operating status. For my analyses, I use one data set, the EPA Biennial Reporting System (BRS) for information on TSDf location and operating status. Given that the RCRA BRS system claims to track all hazardous waste facilities in the U.S. ever operating between 1991 and 2003 (again, approximately 10,196), my colleagues and I opted to use this single reporting system rather than merge multiple waste data sources.

The second difference between my data set and the 608 TSDfs used in earlier studies, is that I gather information on all TSDfs, commercial and non-commercial, as 98% of hazardous waste is generated and stored onsite and therefore permanently disposed of in a non-commercial facility (EPA 1997). Previous TSDf-based national environmental justice studies by United Church of Christ (1987 & 2007) Been and Gupta (1997) and Mohai and Saha (2007) limit their TSDf universe to commercial facilities, arguing that these facilities are more likely to select locations on basis other than proximity to industrial districts – and therefore are more likely to site on race or land value criteria (Lui 2001). Whether or not this is the case, such an exclusion misses 98% of the hazardous waste disposed of in the U.S., and given this loss I opt to include both commercial and non-commercial hazardous waste sites.

Table 4.1. Description, Data Sources, and Summary Statistics for Variables Included in Logistic Regression Analysis Predicting TSDF Presence from 1991 to 2003 by Place-Level Demographic Characteristics in Rural Areas of the U.S.

	Description	Data Source	Mean	s.d.
Dependent Variable				
TSD Present	Binary variable coded 1 if place contains TSD within 1 kilometer buffer	BRS	0.04	0.20
Independent and Control Variables				
<i>Characteristics of Places</i>				
% Hispanic	1990 rate	USBC*	0.03	0.10
% African American	1990 rate		0.06	0.16
% Native American	1990 rate		0.03	0.14
% Renter	1990 rate		0.26	0.13
Median Household Income	1990 measure in dollars		20,572.62	6,639.71
% Unemployed (logged)			1.86	0.68
% Bachelor's Degree or Higher			10.5	7.62
% Below Poverty			0.17	0.11
% Executive, Administrative, and Managerial Occupations			0.08	0.05
% Farming, Forestry, and Fishing Occupations			0.05	0.07
% Manufacturing Occupations			0.20	.014
<i>County Context</i>				
Rural – Urban Continuum	1993 measure of “ruralness” here populations of 250,000 or less selected	USDA	6.63	1.45
<i>Census Regions</i>				
New England			0.02	0.13
Middle Atlantic			0.12	0.32
East North Central			0.17	0.38
West North Central			0.29	0.46
South Atlantic			0.12	0.32
East South Central			0.08	0.27
West South Central			0.13	0.37
Mountain			0.08	0.28
Pacific			0.06	0.24

N = 12,393

USBC = United States Bureau of the Census; USDA = United States Department of Agriculture; BRS = Biennial Reporting System (U.S. Environmental Protection Agency)

*All other non-labeled data sources are US Bureau of Census

Third, my dataset spans from 1991-2003 and I am able to tell which years a given TSDf operates. Again, I do not take advantage of this information in analyses presented in this paper, but more importantly for comparison purposes my aggregated data set spans a larger time period and includes approximately 1,500 facilities that are no longer operating. Fourth, I focus on rural areas rather than urban. The 608 TSDfS used in Mohai and Been's studies are predominantly urban, with 519 metropolitan sites and 89 non-metropolitan sites (Mohai and Saha 2007:358). Therefore, the groups of TSDfS used in each of our studies assess environmental justice concerns in quite different regional contexts.

Fifth, Mohai and Saha used GIS maps to draw circular buffers around each of their 608 TSDfS, whereas my colleagues and I used GIS to draw buffers around places. Mohai and Saha use census tract-level demographic data, and devise two principal techniques for siphoning tract-level data into meaningful buffered proportions: the 50 percent areal-containment method, and the areal apportionment method. The first method is essentially a rule, suggesting that if 50 % of a census tract is contained in a circular buffer of a TSDf, then that tract's demographic data is included in the analyses. The areal apportionment method on the other hand, attempts to take into consideration the proportion of the unit captured in the TSDf's circular buffer. Mohai and Saha (2007: 347) describe the latter method:

Each unit's population is weighted by the proportion of the area of the unit that is captured by the circle. The weighted populations of these units are then aggregated to determine if the demographic characteristics of perfectly circular neighborhoods around the hazard.

The final data set difference is that Mohai and Saha (2007) take a random sample of 519 urban and 89 rural areas to construct a representative non-host comparison sample.

For this project, my population of comparison are rural places whose buffers do not intersect a TSDf facility, where again, places are villages, cities or towns in rural counties (i.e. counties with 250,000 residents or less).

Despite ostensibly having the universe of rural TSDf sites, I justify using inferential statistics in this study on a number of grounds. First, I am confident that the BRS data I collected from the EPA are not comprehensive measures of hazardous waste in the U.S., as previous studies using TSDfs have gathered non-exhaustive tallies from various commercial facility listings (Been and Gupta 1997). Next, my colleague Shushanik Makaryan was only able to geocode (create facility points on GIS maps) for 7,504 of 10,196 total TSDf sites ever listed in EPA BRS databases (due to inadequate address data). Therefore my project does not have a complete population, rather a limited universe with missing data for the years 1991 to 2003⁸.

Results

My replication of Mohai and Saha's (2007) model is presented in Table 4.2, where coefficients are juxtaposed and differences in variable measurement are noted in bold. Overall, Mohai and Saha (2007) and my analyses indicate that African American and Hispanic populations live in closer proximity to hazardous waste than would be expected under random conditions. Our findings diverge for the income, poverty, unemployment and education measures. Median household income is positively associated with the presence of hazardous waste, whereas in Mohai and Saha's model

⁸ Given time constraints, exploration of non-precisely geocoded TSDfs has not been done. Such analyses would indicate whether missing data is biased or not, and will be completed when this paper is prepared for publication.

Table 4.2. Comparison of logistic regression coefficients in Mohai and Saha (2007) with those found in this study, both use dependent variable TSDf presence.

<u>Mohai and Saha (2007)</u>	<i>Coefficient and Level of Significance</i>		<u>Richter</u>
Percent African American	5.41 ***	1.06 ***	Percent African American
Percent Hispanic	3.11 ***	1.70 ***	Percent Hispanic
Mean Household Income (logged)	-5.16 ***	0.80 ***	Median Household Income (logged)
Percent Below Poverty	-8.50 ***	-0.24	Percent Below Poverty
Percent Unemployed	4.18	0.02 *	Percent Unemployed
Percent with College Degree	1.30	0.05 ***	Percent with Bachelor's Degree of Higher
Percent Employed in Exec., Managerial & Professional Occup.	5.36 **	2.82 *	Percent Employed in Exec., Managerial & Administrative Occup.
Percent Employed in Precision Production, Trans., or Labor Occup.	2.78 **	2.96 ***	Percent Employed in Manufacturing Occup.
Constant	5.78 ***	-16.38 ***	Constant
-2 Log Likelihood	1511.8	2065.7	-2 Log Likelihood
Mode chi-2 (df = 10)	171.124 ***	244.61 ***	Mode chi-2 (df = 8)
N = 1216 circular neighborhoods			N = 12,369 rural places

*p<0.05, **p<0.01, ***p<0.001

Note: Both use 1990 census data, however Mohai and Saha (2007) use 1 mile radius around TSDf sites and I use 1 kilometer buffer around each rural census place. Additionally, the TSDf sample used by Mohai and Saha (2007) excludes Alaska, whereas this study includes Alaska.

mean household income is negatively associated with presence of hazardous waste⁹. Percent below poverty is not significant in my model, though it has a strong negative relationship with presence of hazardous waste in Mohai and Saha's model. Next, percent unemployed is positive and significant in my model, whereas it is not significant in the other. Finally, percent with bachelor's degree or above is positive and significantly related to presence of a TSDf in this model, whereas Mohai and Saha's measure "percent with college degree" is not significant.

Though there are numerous differences between the datasets compared, their juxtaposition illustrates a number of interesting things. First, the positive relationships between income, education and TSDf presence in my model, may speak to the more inclusive TSDf universe I constructed in comparison to Been and Gupta's and Mohai and Saha's 608 commercial facilities. As mentioned previously I include all TSDfs (both onsite generator/managers and offsite receivers) over a longer time period (1991-2003 vs. mid-late 1990s for Mohai and Saha). This inclusion means that my dataset captures more production and manufacturing areas than a TSDf dataset with only offsite receivers. My TSDf dataset is highly correlated with places having improved economic and social conditions, while also having higher unemployment. This key distinction between my TSDf universe and Mohai and Saha's dependent variable universe, may account for the positive significance of household income and percent with a bachelor's degree or greater. This indicates that a baseline of economic growth is present in places with hazardous waste, a finding similar to that made by Downey (2003) – where the

⁹ As indicated above, I used median household income whereas Mohai and Saha use mean household income. Both measures are logged, however our different levels of measurement further challenge precise comparability between our models.

author finds that areas of Detroit with higher pollution emissions have increased manufacturing jobs.

Furthermore, the inclusion of manufacturing waste in my TSDF dataset enables me to ask if spatial inequality differs for TSDF facilities that only receive waste versus those that both produce and store waste. My findings show that environmental inequality persists net of control variables and urban-rural context, as African American, Hispanic, and blue collar populations continue to be strong predictors of hazardous waste siting. This dual race and class finding persists in my next set of logistic regression analyses, where categorical environmental justice measures are used in extended models of varying buffer distance.

CHAPTER FIVE: RESULTS

Overview of Chapter 5

This chapter contains three logistic regression analyses that further explore spatial aspects of both environmental justice theory and treadmill of production concerns over distributions of environmental “bads.” All three analyses use categorical measures of five selected environmental justice variables: Hispanic, African American, Native American, renter and population below poverty. First I perform logistic regression of TSDF presence on an extended model (compared to Mohai and Saha’s replicated model used in Chapter 4) which includes additional race, regional and control variables. Second, I perform logistic regression of TSDF presence for each buffer size (0, 1, and 3 kilometers). This enables comparison between demographic characteristics of those places with hazardous waste within their borders versus places with waste within 1 and 3 kilometers. Finally, I perform logistic regression on three versions of my environmental justice variables, categorizing these variables at 10, 25, and 50 percent proportions of total place population. This enables comparison of each environmental justice variable at varying proportion value, yielding insights into thresholds at which certain race/class variables no longer predict TSDF presence. These analyses address research questions concerning the predictive importance of race and class in understanding the spatial distributions of hazardous waste in the U.S.

Descriptive Statistics

To begin I provide an updated descriptive data table, displaying the mean and standard deviation of the five environmental justice indicators I selected (Table 5.1).

Table 5.1. Description, Data Sources, and Summary Statistics for Variables Included in Logistic Regression Analysis Predicting TSD Presence from 1991 to 2003 by Place-Level Demographic Characteristics in Rural Areas of the U.S.

	Description	Data Source	Mean	s.d.
Dependent Variable				
TSD Present	Binary variable coded 1 if place contains TSD within 1 kilometer buffer	BRS	0.04	0.20
Independent and Control Variables				
<i>Characteristics of Places</i>				
<i>Hispanic 10</i>	<i>Binary variable coded 1 if place population is 10% or more Hispanic</i>	USBC*	0.09	0.29
<i>African American 10</i>	<i>Binary variable coded 1 if place population is 10% or more African American</i>		0.16	0.36
<i>Native American 10</i>	<i>Binary variable coded 1 if place population is 10% or more Native American</i>		0.05	0.23
<i>Renter 10</i>	<i>Binary variable coded 1 if place contains 10% or more Renters</i>		0.92	0.27
<i>Percent Below Poverty 10</i>	<i>Binary variable coded 1 if place population is 10% or more below poverty</i>		0.73	0.07
% Unemployed (logged)			1.86	0.68
% Bachelor’s Degree or Higher			10.5	7.62
% Executive, Administrative, and Managerial Occupations			0.08	0.05
% Farming, Forestry, and Fishing Occupations			0.05	0.07
% Manufacturing Occupations			0.20	.014
<i>County Context</i>				
Rural – Urban Continuum	1993 measure of “ruralness” here populations of 250,000 or less selected	USDA	6.63	1.45

N = 12,393

USBC = United States Bureau of the Census; USDA = United States Department of Agriculture; BRS = Biennial Reporting System (Conducted by U.S. Environmental Protection Agency)

*All other non-labeled data sources are US Bureau of Census

Note: Census regions were included in this analyses however are not reported in the table.

Comparing means and standard deviations for rate versus categorical environmental justice variables illustrates a few interesting characteristics about the variable distributions. Rural place population means for Hispanics and African Americans remain in the single digits when these variables are categorized as continuous or discrete proportions. Proportion Native American has only a 2 % variation between its mean as a continuous rate and discrete proportions (3 % and 5 % respectively). On the other hand, renters show large variation, with the rate having a mean of 26 % and the discrete proportion having a mean of 92 %. Proportion below poverty behaves in a manner similar to renters, the rural U.S. average number of persons below poverty in a place is 17 %, whereas the average is 73 % in rural places where ten percent of the population is impoverished.

Full Model Logistic Regression at 1 Kilometer

The results for control measures indicate that places with TSDFs contain a baseline level of economic productivity, as indicators of manufacturing and executive employment have positive and significant coefficients (see Table 5.2 for results). However, these are also places positively related to higher education levels and unemployment, while negatively related to farming, forestry and fishing occupations. Regarding the selected environmental justice variables, my findings support trends observed in recent quantitative environmental justice analyses, essentially finding both race and class measures to be significant predictors of hazardous waste. As I do not employ longitudinal aspects of the TSDF dataset here, I was not able to test how race or class might relate to places with growth or decline in hazardous waste between 1991 and 2003.

Net of control variables, proportion Hispanic, African American, renter, and persons below poverty all have significant positive effects on TSDf presence in or near a rural place. Specifically, rural places that are at least 10 percent or more Hispanic, are 1.59 or approximately one and a half times more likely to have a hazardous waste facility than places with Hispanic populations below 10 percent. Nearly the same interpretation applies to places that are 10 percent or more African American, as such places are 1.90 or approximately twice as likely to have a hazardous waste facility than places with African American populations below 10%. African American populations are slightly stronger predictors of rural hazardous waste presence in a place than Hispanic populations, which may in part be due to rural African American populations being larger than rural Hispanic ones: in 2000, nonmetropolitan African American population was 4.9 million while the nonmetropolitan Hispanic population was 3.2 million (Lichter et al., 2007).

However, places with proportions of Native Americans at 10% or greater are negatively related to TSDf presence between 1991 and 2003. This is likely due to the lack of production and manufacturing near Native American places (the correlation coefficient between percent Native American and percent manufacturing occupation by place is -0.15). Places with a 10% or greater proportion of renters are 7.81 or almost eight times more likely to have a TSDf than places with less than 10%. Places with 10% or greater proportion of persons below poverty are 1.22 times more likely to have a TSDf present than places with less than 10% below poverty.

These results show that rural patterns of environmental injustice are parallel to those found in urban areas. Similar to findings by Been and Gupta (1997) and Mohai and Saha (2007) in their national studies of TSDFs, Hispanic and African American

Table 5.2 Logistic Regression of TSD Presence from 1991-2003 on Environmental Justice Predictor Variables for Places within 1 Kilometer of a TSD facility.

Variables	Coefficient	Log Odds	Significance Level
<i>Characteristics of Places</i>			
Hispanic 10 percent or greater	0.44 (0.21)	1.55	0.038
African American 10 percent or greater	0.50 (0.14)	1.64	0.001
Native American 10 percent or greater	-1.47 (0.36)	0.23	0.000
Renter 10 percent or greater	2.11 (0.46)	8.24	0.000
Below Poverty 10 percent or greater	0.20 (0.12)	1.22	0.091
% Unemployed (logged)	0.28 (0.09)	1.32	0.001
% Bachelor's Degree or Higher	0.05 (0.01)	1.05	0.000
% Executive, Administrative, and Managerial Occupations	2.48 (1.09)	26.26	0.001
% Farming, Forestry, and Fishing Occupations	-20.86 (2.13)	--	0.000
% Manufacturing Occupations	2.45 (0.42)	11.53	0.000
<i>Census Regions (New England Dropped)</i>			
Middle Atlantic	-1.35 (0.30)	0.08	0.000
East North Central	-0.36 (0.24)	0.69	0.123
West North Central	-0.68 (0.25)	0.50	0.005
South Atlantic	-1.26 (0.27)	0.28	0.000
East South Central	-0.57 (0.27)	0.57	0.033
West South Central	-0.46 (0.27)	0.63	0.085
Mountain	-0.48 (0.28)	0.61	0.081
Pacific	0.05 (0.29)	0.95	0.872
Constant	-6.27 (0.59)		
Pseudo R-Square	0.12	-	
LR chi2(20)	519.01	-	0.000
N = 12,368			

populations are significantly spatially related to hazardous waste – even when economic and regional contexts are taken into account. My findings also corroborate treadmill of production predictions, namely that the effects of production and concomitant waste production are disproportionate waste dispersal on low-income and minority populations.

Downey's 2003 and 2007 findings in spatial analyses of Detroit, suggest similar environmental justice processes may be taking place at different spatial scales. When Downey aggregated TRI (Toxic Release Inventory) data on polluting facilities in Detroit, he found that at the census tract level, income was the strongest predictor of proximity to a polluting facility. However, when he used smaller-scale distanced based methods, he found that percent African American had a stronger significant effect on proximity to polluting facility. This finding is similar to that made by Mohai and Saha (2007), where spatial analyses used on smaller spatial scales produce stronger correlations for race, class and, in this case, hazardous waste. Though my analyses are different from Downey (2007) and Mohai and Saha's (2007), in rural regions similar patterns with regard to race and class are found at the place-level. As shown in the next set of results, spatial analyses of places with TSDFs either in their borders or within 1 or 3 kilometers, have significant positive relationships with race and class measures.

Logistic Regression at 0, 1 and 3 Kilometer Buffers

To examine the effects of TSDF distance on demographic characteristics, I include logistic regression analyses for varying buffer distances. First, looking at Table 5.3, it is clear that the size of the place buffer (at either 0, 1 or 3 kilometers) has a large

Table 5.3 TSDF Counts at Different Buffer Distances for Urban and Rural Places in the U.S.

<i>Buffer Distance</i>	<i>TSD Facilities Total</i>	<i>TSD Facilities in Rural Areas</i>
0 km	1, 868	412
1 km	2,710	531
3 km	4,048	692

Source: EPA Biennial Reporting System 1991-2003

impact on the number of TSDFs captured in the dependent variable (TSDFs within a place buffer). For example, the 0 kilometer buffer of rural places contains 412 TSDFs, and the 3 kilometer buffer of rural places contains 692 TSDFs (and both of these numbers are smaller than their urban counterparts).

Results for logistic regression analyses (using the full model from Table 5.2) for 0, 1 and 3 kilometer datasets are found in Table 5.4. That is, all rural census places, buffered at three distances, where each place buffer is intersected with TSDF locations to create a new spatial data set in GIS. When Hispanic, African American, Native American, renter and persons below poverty are all categorized as 10 % or greater proportions in the 0 kilometer buffer, all five variables are significantly related to presence of TSDF in a rural place. All variables except proportion Native American are positive, and their coefficients are all largest at the 0 km buffer. Comparing coefficients for these variables across buffer sizes, it is clear that these race and class measures are strongest for places with TSDFs within their boundaries (i.e. for the 0 km buffer) – seen most dramatically in the renter variable. Places with at least 10% renters are approximately 10 times more likely to have a TSDF present within their borders, than

Table 5.4. Coefficients, Odds Ratios, and Level of Significance for Logistic Regression of Environmental Justice Categorical Predictors on 1991 -2003 TSDF presence - by 0, 1, and 3 km Buffer Distance.

Variables	Coefficient	Odds Ratio	Significance Level
<i>Hispanic 10</i>			
0 kilometer buffer	0.48	1.62	0.037
1 kilometer buffer	0.44	1.55	0.038
3 kilometer buffer	0.39	1.48	0.039
<i>African American 10</i>			
0 kilometer buffer	0.55	1.74	0.001
1 kilometer buffer	0.50	1.64	0.001
3 kilometer buffer	0.44	1.55	0.001
<i>Native American 10</i>			
0 kilometer buffer	-1.31	0.27	0.001
1 kilometer buffer	-1.47	0.23	0.000
3 kilometer buffer	-1.73	0.18	0.000
<i>Renter 10</i>			
0 kilometer buffer	2.36	10.65	0.000
1 kilometer buffer	2.11	8.25	0.000
3 kilometer buffer	1.59	4.93	0.000
<i>Percent Below Poverty 10</i>			
0 kilometer buffer	0.23	1.26	0.078
1 kilometer buffer	0.20	1.22	0.091
3 kilometer buffer	0.01	1.01	0.908
N = 12, 368			

Note: Only selected environmental justice variables shown, though full models (as detailed in Table 5.2) were run for each buffer size.

places with less than 10% renting population at 0 kilometers. This pattern matches similar results found by Mohai and Saha (2007), where percent Hispanic and African American become significant on smaller spatial scales (for them, within a 1 mile radius of the TSDF compared to census tracts in a predominantly urban study). Places with 10% or greater proportions of Native Americans are negatively related to presence of TSDFs. Places with 10% or greater proportions of persons below poverty are positively associated with TSDFs at the .01 level for the 0 and 1 kilometer buffers.

Logistic Regression with Categorical EJ Variables at 10, 25, and 50 % Proportions

Table 5.5 presents results for logistic regression models run with varying proportions (10, 25, and 50 %) for Hispanic, African American, Native American, renter and persons below poverty by place. As the results indicate, the five variables are significantly related to presence of rural TSDFs. Hispanic, African American and renter proportions are all positive and significant at 10 and 25 % proportions. Places with proportions of Native Americans, African Americans, and Hispanics above 50% are not significantly related to TSDF presence. This finding may indicate either that there are few rural places with proportions of these variables above 50 %, or that these places are unlikely to have TSDFs present – perhaps due to place size or lack of manufacturing industry. Places with proportions of persons below poverty above 10% are 1.22 times more likely to have hazardous waste present, however proportion below poverty becomes significantly negatively related to TSDFs at the 25% or greater level. This indicates, again, that there appears to be a baseline level of economic activity in a rural place in order for TSDFs to be present. Once again, my findings most closely corroborate with

Downey's (2003) spatial analysis of TRI emissions in Detroit, where waste follows economic activity. That said, this activity is always tightly coupled to the historic and contextual process of racist housing discrimination and structural prejudice in the U.S.

Table 5.5 Coefficients, Odds Ratios, and Level of Significance for Logistic Regression of Environmental Justice Predictors on 1991 -2003 TSDf presence - by 10 %, 25 %, and 50% Population Percentage at 1km Buffer.

Variables	Coefficient	Odds Ratio	Significance Level
<i>Hispanic by proportion</i>			
10% or <	0.44	1.55	0.038
25% or <	0.74	2.10	0.008
50% or <	0.66	1.94	0.109
<i>African American by proportion</i>			
10% or <	0.50	1.64	0.001
25% or <	0.39	1.47	0.020
50% or <	-0.025	0.98	0.919
<i>Native American by proportion</i>			
10% or <	-1.47	0.23	0.000
25% or <	-1.95	0.14	0.001
50% or <	-2.35	0.10	0.001
<i>Renter by proportion</i>			
10% or <	2.11	8.24	0.000
25% or <	1.48	4.39	0.000
50% or <	0.35	1.42	0.082
<i>Percent below poverty</i>			
10% or <	0.20	1.22	0.091
25% or <	-0.80	0.45	0.000
50% or <	dropped		

N = 12, 368

Note: Only selected environmental justice variables shown, though full models (as detailed in Table 5.3) were run for each proportion shown.

CHAPTER SIX: DISCUSSION AND CONCLUSION

This thesis has employed spatial data and GIS analytic techniques in the rural U.S. Results reveal striking parallels with environmental justice studies conducted at national and city levels. I address the following environmental justice research questions: 1) Are places with higher concentrations of Hispanic, African American and Native American populations positively correlated with TSDF presence? 2) Are places with higher concentrations of renters (serving as measure of class here) and individuals living below poverty positively correlated with TSDF presence? These analyses provide evidence that places with high proportions of Hispanics, African Americans, renters and impoverished populations all significantly predict hazardous waste disposal in the rural U.S. These results largely corroborate extant spatial environmental justice analyses, specifically recent work by Mohai and Saha (2007) and Downey (2003). While changing the scope of previous studies in four significant ways (place-based spatial data set, expanded TSDF universe, wider set of operation dates, and rural regional focus) findings in quantitative environmental justice research persistently show that it is low-income, non-whites that bear disproportionate environmental burdens in the U.S.

This study makes a significant methodological and theoretical contribution by expanding the universe of TSDFs to include both offsite receivers and onsite producer/disposers of waste. This inclusion drastically changes the size and spatial dispersion of the TSDF population under study. Whereas previous studies use a TSDF data set of offsite receivers mostly located in urban areas, my inclusion of onsite producer/disposers brings in rural manufacturing sites. Therefore theoretical

environmental justice questions should shift towards a focus on how and why manufacturing is distributed in patterns found today.

By focusing on rural areas of the U.S. this study expands the discussion of environmental justice to places and spaces with different characteristics than urban areas. I find that, compared to African American and Hispanic populations, Native Americans are negatively related to place-based hazardous waste. Class indicators, renters and persons below poverty in strong manufacturing regions are significant predictors of TSDF presence, arguably due to my inclusion of onsite hazardous waste generators in my dependent variable. This likely contributes to the finding that places with economic activity and significant minority populations house hazardous waste. Overall, this paper widens quantitative environmental justice studies to-date, arguing that rural onsite waste presents a sizable burden. Furthermore I contribute empirical evidence to theoretical discussions of race and “life chances,” though my proximity analyses are no certain indication of pollution exposure, they are at least an important contributor to our growing understanding of environmental causes of sickness. This situation is especially pertinent given that it is known that low-income and minority populations suffer from higher rates of illness and poorer healthcare services.

Future national-level research should analyze TSDFs in both rural and urban areas at the census block or tract-level, perhaps using Saha and Mohai’s areal apportionment technique to weight demographic and economic data in spatial analyses (taking advantage of census data available at the smallest scale available). Though my data set attaches year information to each TSDF for all EPA biennial reports, I was not able to take advantage of this information for a number of reasons (including changing

definitions of hazardous waste, and inclusion of variables that are optional in some years and required in other years among others). Future studies could take advantage of an improved TSDf year-based data set to explore those places that receive new hazardous waste sites between 1991 and 2003 – in addition to those that lose hazardous waste sites (however this would entail extensive investigation to assure data reliability, given the EPA’s poor job of doing so themselves).

There remain unexplored questions regarding the ‘winners’ in environmental distribution studies, which might shed light on the continuing debates over the mechanisms behind race and class-based discrimination in the United States. Specifically, future studies could test whether places that have lost hazardous waste facilities are places with higher median incomes and higher proportions of white populations. Furthermore, manufacturing and its attendant waste production can no longer be discussed in only national contexts. Between 1991 and 2003 over 1,500 TSDFs close permanently in the U.S., and the number of operating TSDFs is decreasing. This disappearance of hazardous waste in the U.S. likely reflects recent trends in economic globalization, where U.S. manufacturing (and hazardous waste) are largely relocating in poorer nations.

Finally, environmental justice scholars must continue their collaboration across disciplines and methodological orientation, given each of our limited range of expertise. Increasing collaboration between social scientists and natural scientists, such as epidemiologists – and furthermore medical geographers and impacted communities themselves, can only aid in strengthening our knowledge and ability to combat environmental injustice.

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