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TGIS 415

Final Paper

Environmental Justice (or Injustice?) in Pierce County

Introduction

In our society, it has been observed time and time again that minority populations and those living in poverty shoulder a disproportionate burden of negative environmental effects. Numerous case studies support this claim (Blodgett 2006; Bullard *et al*. 2007; Mennis 2002; Sicotte 2008). Whenever there is a significant disparity of socioeconomic status (SES) between populations, there is potential for one group to be underrepresented. Minorities and the poor have a tendency to be found in areas with adverse environmental conditions (Bullard et al. 2007). A case study by Bullard et al. (2007) shows that areas with high numbers of toxic sites have a much higher number of people in poverty and higher ratios of minorities living nearby than do areas with far fewer toxic sites. When one group of people disproportionately shoulders an environmental burden, environmental injustice is occurring. The EPA defines environmental justice as “the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies” (2012). So when a group of people is not treated fairly, environmental justice is not being carried out.

Multiple studies have fallen to using GIS as a means of identifying patterns of environmental injustice in a geographic area. GIS is useful for identifying this community problem because it is an inherently spatial problem (Mennis 2002). However, the problem is a bit of a “chicken or the egg?” question. Are areas allowed to harbor more hazardous facilities because the people living there are underrepresented and do not have an active enough voice to resist new sites? Or do areas with hazards attract people of low SES because property values decline so those people can afford housing? One study supports the claim that hazardous facilities enter a neighborhood because of environmental racism (Sicotte 2008).

When conducting a study to evaluate the environmental justice of an area, many factors come into play (Harner *et al*. 2002). It is important to identify areas of varying SES rather than solely areas with varying income level or poverty rates because highly distressed areas will have more than one variable contributing to distress. In most studies, race, income and poverty are primary demographic factors included in analyses. Some other factors include people with a language barrier (Johnson & Kirk 2004) and education level, i.e. a rate of people without a high school diploma (Blodgett 2006).

In addition to juxtaposing environmental hazards to areas of varying SES, observing how children and the elderly are affected is a worthy cause (Johnson & Kirk 2004; Landrigan *et al*. 2010; Wu & Batterman 2006). Oftentimes, the elderly and children in areas of socioeconomic distress are the most affected (Johnson & Kirk 2004; Landrigan *et al*. 2010). Asthma rates, obesity and lead poisoning have increased in populations of children in the past few decades (Landrigan *et al*. 2010). So when a population is adversely affected by environmental injustice, the children are especially vulnerable because they are so much more affected by chemicals (Landrigan et al. 2010). The elderly may be susceptible, as well, because of more sensitive immune systems. Therefore, observing the proximity of elderly and children to hazards areas may reveal some informative patterns.

This study will focus on identifying patterns of environmental justice in Pierce County. This will be accomplished by: constructing a SES index based on a variety of demographic variables, locating and rating hazardous facilities in the county, identifying locations where the elderly and children frequent (such as schools, nursing homes, parks and daycares), and isolating clusters of high and low income, high and low levels of people below the poverty line, and high and low ratios of minority populations. The hazardous locations will be analyzed against all of the other factors.

My hypothesis is that there will be significantly more hazards in areas of low SES than in areas of high SES. As well, I hypothesize that locations with children and the elderly in low SES areas will be closer to a higher ratio of hazards than similar locations in areas of high SES. In addition, I think I will find that even in observing median income, poverty and minority clusters against hazards separately it will show a pattern of increased hazards in areas with distressed income and poverty levels and high minority populations. Overall, I expect to find patterns of environmental injustice in Pierce County.

Methods

Since this project is about attempting to identify a trend of environmental justice (or injustice) in Pierce County, the first step was to collect the data that accurately paints a picture of hazards and SES in the county. To construct a SES index, multiple variables were determined to be of importance. The variables selected were median income, unemployment, linguistic isolation, race, poverty, tenure, and educational attainment. The variables were obtained from the 5-year estimates (2006-2010) for the Census' American Community Survey (ACS). Each variable's table ID was downloaded through the Excel summary retrieval tool macro. Each variable and its table ID is listed in figure 1. The Pierce block group shapefile, for joining to the Census data, was obtained from Tigerline.

Variable	Table ID
Median Income	B19013
Employment Status	B23007
Linguistic Isolation	B16002
Race	B02001
Poverty	B17021
Tenure	B25003
Educational Attainment	B15002

Figure 1. Census ACS 5-year Estimates (2006-2010) for demographics used in this paper's analysis.

Once a table was retrieved from the macro, the Estimates tab was sorted by 'GeoName' to contain the words 'Pierce' and 'block' so that the data for Pierce County block groups was isolated. All of the data was added to a new Excel workbook. Then the Geography tab was sorted to contain only Pierce County. The isolated data was added to the same new workbook. Both the Estimates and Geography tabs contain irrelevant columns. For Estimates, all fields except 'LOGRECNO' and the relevant variable data were deleted. For Geography, all fields except 'LOGRECNO' and 'GEOID' were deleted. For all variables, 'GEOID' had to be manipulated to contain only the 12 digits that allow the table to be joined to Pierce block group polygons. To fix the existing ID, the Excel equation '= (right(X, 12)' was used and the new field was named 'GEOID2'. To make it a permanent fix, the column was copied and pasted as a value, and the two extra ID fields were deleted. Each variable's Estimates table had also to be manipulated to contain a rate, except for median income. For each, the relevant field was divided by the total. All 7 tables were imported into the project geodatabase and the Pierce block groups shapefile was imported into the SES feature dataset.

The Geography and Estimates tables for each variable were joined by the 'GEOID2' field. Then a new field was added and filled with the field calculator by the equation '((variable rate-variable mean)/variable standard deviation)'. This gives the standardized score for each variable and is the variation of each rate from the mean. All of the variable tables were joined together using 'GEOID2' as the join field. All duplicate fields were turned off and the table was exported to make the join permanent. Each variable was classified based on the variation from the mean. A simple field calculation yielded a cumulative score for each block group. The range was from -10 to 7, where a score of -10 signifies extreme socioeconomic distress and a 7 signifies relative prosperity. The socioeconomic index was visualized with a red to green chloropleth map. The classification breaks were standard deviation with 6 breaks and 1 standard deviation. High SES areas were 1.5 standard deviations above the mean, and low SES areas were 1.5 standard deviations below the mean.

Hazard sites can be identified for a range of severity. Superfund sites and toxic release sites are hazards, but dry cleaners and gas stations can generate hazardous waste too. Initially, this project was going to focus only on the Environmental Protection Agency's (EPA) Toxic Release Index (TRI) for the hazard analysis. However, in Pierce County, there are only about 80 sites. That was determined to be an inadequate number of sites for identifying a trend of environmental justice in the whole county. The Department of Ecology (DOE) has a GIS facilities database with tables for different hazard programs. TRI sites were included. The DOE facility/site programs selected for this project were state clean-up sites, hazardous waste generators, industrial sites, landfills, leaking underground storage tanks (LUST), hazardous waste storage sites, federal superfund sites, tier 2 hazardous sites, hazardous waste transfer sites, and TRI sites. The facilities are defined in figure 2.

Facility Type	Definition
Clean-up	A site being cleaned up under state regulations
Generator	Facilities that generate a small, medium, or large quantity of hazardous waste in a month
Industrial	Facilities that are one of three types of industry: aluminum smelters, oil refineries, or pulp and paper mills
Landfill	Facilities where solid waste is disposed of on or in the land and is not treated
LUST	Leaking underground storage tanks that are being cleaned up
Storage	Facilities that treat, store, or dispose of hazardous waste
Superfund	A federal clean-up site for existing superfund sites
Tier 2	Businesses that store high levels of hazardous chemicals or a small amount of extremely hazardous chemicals on site at one time
Transfer	Sites that receive waste, transfer waste from one vehicle to another or from one container to another, or stores waste in a vehicle or on site for 10 days or less
TRI	Facilities that make, process, or use a level of toxic chemicals above a threshold assigned to each chemical

Figure 2. Data definitions for DOE hazard sites.

All of the tables obtained from DOE include site names, facility/site ID numbers, and addresses for geocoding. The tables were combined into one table; duplicate entries were not added to the new table. The 10 tables yielded about 2,000 hazard sites. In order to geocode the addresses, an address locator was created. Upon geocoding, seventy-five percent of the entries were successfully matched to a location. The rest were ignored because many of the unmatched addresses did not contain real addresses, but rather were descriptions of locations.

Since the DOE does not provide any way for separating the worst sites from the least harmful, an arbitrary classification procedure was created. Each individual DOE hazard table was added to the geodatabase and joined to the geocoding result table, using the facility/site ID as the join field. All records were kept which resulted in a number of 'null' values in each column. The idea was that a site could be determined to be more harmful if it were present on multiple tables. Using the field calculator, all of the 'null' values were changed to '0' and all of the values with a record were given a value of '1' for each hazard facility type. Industrial sites, superfund sites and TRI sites are the nastiest of the lot, so they were more heavily weighted with a value of '2' for being present in a table. A new field was added and filled with the field calculator to contain the cumulative score of all 10 tables. Therefore, with 7 tables with a maximum weight of '1' and 3 tables with a maximum weight of '2', the absolute maximum value was a '13'. It turns out that the maximum value was '7' and the lowest possible value was '1'. To isolate the nastier of the hazards points, sites with a cumulative value of '3' or more were exported as a separate set of points. That value was chosen as the cut-off because a '3' means that a site is either present on 3 or more tables or is present on one of the doubly weighted tables, along with one other table.

As mentioned before, in an analysis of this type, observing the effects on children and the elderly is worthwhile. For this study, point features for daycares, schools, parks, nursing homes, adult family homes, and boarding homes were collected. The idea here was that these locations are where children and the elderly are often present. These points were merged into one feature class. Although this generalizes the data, the overarching idea was to identify a broad pattern of injustice. With the highest SES areas selected, points falling within the area were also selected and exported as high SES points. The same was done for low SES points. A buffer of 400 m was applied to the high and low SES points. 400 m was selected as the buffer distance because it is recommended distance to apply to sites to safely separate them from sources of toxic and hazardous generation (ICF 2005). Then the aerial density of the hazard points located within the buffer zones was calculated. The areal density was also calculated for the number of hazards present in areas of low and high median income, low and high poverty rates, and low and high minorities.

A final project implementation was to conduct a hot spot analysis of the hazard points with regards to a raster of the SES index. The hot spot raster was reclassified to only have 4 values. The highest density polygons were exported so that only the worst areas were viewed. Zonal statistics was run to find the absolute worst area in Pierce County, in terms of density of hazards and low SES.

Results

The analysis of the SES index reveals a great disparity in the number of hazards between lowest and highest SES areas. In the block groups where SES is 1.5 standard deviations above average (i.e. high SES), there is a grand total of one hazard site. As well, the site is not a bad one. It has a score of ‘1’, which means it is only a hazardous waste generator. On the other hand, in the block groups where SES is 1.5 standard deviations below average (i.e. low SES), there are 304 hazard sites with scores ranging from ‘1’ to ‘6’. The hot spot analysis resulted in the identification of a neighborhood where the SES and hazards combined to theoretically make up the worst environmental area in the county. The area identified is directly south of Highway 16 and west of I-5 where the two meet. South Tacoma Way cuts across the area and S. 38^{th} St. borders the bottom boundary of the neighborhood.

The school, daycare, nursing home, and park analysis revealed that there are no hazards within the 400 meter buffer for locations in high SES areas, while there is an abundance of hazards in the buffer of low SES locations. The areal density of hazards in the high SES location buffer is, therefore, zero hazards per square mile. On the other hand, the areal density of hazards in the low SES location buffer is 0.002832 hazards per square mile. Within the identified worst area in Pierce County are a variety of daycares, schools, nursing homes and parks with a multitude of hazards falling within their 400 meter buffers.

The analysis of hazards in areas of high and low median income revealed areal densities of 0.000037 and 0.0001, respectively. So there are nearly three times more hazards per square mile in areas of low median income. For areas of high and low poverty rates (where a high poverty rate signifies a high number of people living in poverty), the areal densities are 0.001207 and 0.000125. There are almost ten times more hazards per square mile in areas of high poverty. And for areas of high and low rate of minorities, the areal densities are 0.001659 and 0.000072. That means that there are about twenty-three times more hazards per square mile where there are higher populations of non-white in the community.

Discussion

With three separate analyses showing patterns of environmental injustice, it can be concluded that there is environmental injustice occurring in Pierce County. The SES index overlaid with the locations of hazards reveals a shocking contrast. It is very obvious that those living in low SES live in closer proximity to hazard sites than those living in areas of high SES. The thing that needs to be noted here, though, is that there are missing pieces to the puzzle. This project shows a snapshot in time. It does not take into account the change over time. As mentioned before, it is the question of "which came first, the hazards or the socioeconomically distressed?"

It would appear that the elderly and children in low SES—as projected by the locations of schools, daycares, nursing homes, and parks—would be more adversely affected by hazards than the elderly and children in high SES. It also appears that the rate of minorities in a community is the strongest indicator of whether there will be a hazard nearby or not. The areas with low minorities have the lowest density of hazards, while the areas with high minorities have the highest density of hazards.

Poverty rate is the second strongest indicator, followed by median income. This pattern fits with the case study outlined by Bullard et al. (2007).

Critical Analysis

The approach to this research was purely quantitative and somewhat reductionist. Although there is a revealed pattern of environmental injustice in Pierce County, it is important to take into consideration that much data was aggregated and simplified. Another person conducting this research could have taken the same data and made different judgment calls about how to portray or analyze the data using GIS. As Pickles (1995) discusses, one must be critical of using GIS for addressing spatial problems.

This research does not take into account the average SES areas. It may be that if the average SES areas were included in the analyses, there may not be such an obvious pattern of disparity between average and low SES. On the same line of thought, this project was only searching for negative environmental features; the search was for environmental injustice. But as Al-Kodmany (2000) writes, "Strength-focused assessments represent an improvement over traditional community assessment processes and, in the hands of creative community organizers, they can be much more powerful." This project could have taken on a whole different focus if the search had been for positive environmental features in the community.

The classifications for the hazard data are somewhat arbitrary and the sites have not been ground-truthed. Some of the hazards are things that actually might be desirable in a community, such as hospitals, pharmacies, and schools. However, there are some sites of this kind that have been classified as a high as a '3' (e.g. Sumner High School and Saint Joseph Medical Center). For the purpose of this project, that fact was glossed over and these hazards were left alongside hazards that truly are worthy of a score of '3' and are undesirable in a community. However, as Monmonier points out again and again, maps are created based on judgment calls or biases about what information should be portrayed to make a point (2005).

It would be wise, in a future study of this type, to include qualitative data to add a story to the quantitative data. Surveys in the community about sites that are particularly undesirable could help in ground-truthing the DOE hazard sites. There are probably countless ways to approach the addition of qualitative data. Pavlovskaya makes a good argument for using qualitative and quantitative data for uncovering patterns (2006). She writes, “Qualitative methods, on the other hand, work to understand social worlds in their complexity and contradiction, although a certain reduction is unavoidable… Qualitative methods help to uncover geographic processes that simply cannot be revealed by quantitative analysis alone” (2006). Using qualitative data in a continuum with quantitative data may reveal something completely different than what was discovered above.

Acknowledgements

I would like to thank Dr. Matt Kelley for his guidance throughout this research project. I would also like to thank Natasha Boyde for her assistance during the implementation and visualization stages. My group members, Gina Owens, Rebecca Solverson, and Robert Leavitt, were invaluable for the brainstorming process, so I would like to thank them too. Eric Lane drew my attention to the Department of Ecology data source, without which, there would be no hazard data. Melora Shelton, Nannette Huber, Stacey Curry, and Lisa Bruce were exceptionally helpful and patient when I needed assistance with the Census data collection. I would finally like to thank the 2011-2012 GIS certificate program cohort for feedback and camaraderie.

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