

Do You Know How Safe Your Air Is?

Validation of a Survey Measure of Perceived Air Quality

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Abstract

Concern about the health effects and environmental justice implications of air pollution is widespread, but there is almost no relating pollution with demographic characteristics. It is not known whether people are aware of or able to accurately assess their risks, although perception of risk level is likely a factor in neighborhood choice. Given challenges in using objective data about air pollution, perceived measures may also be useful in survey research seeking to predict health outcomes. This paper first investigates the relative contributions of individual sociodemographic characteristics and personality, neighborhood socioeconomic status, industrial and transportation land uses, and proximity to traffic and major industrial sources of pollution to individual perceptions of air quality in Chicago. Analysis then compares perception with available objective data on air pollution risk.

Background

Our collective choices as a society about how to meet our basic needs have important consequences for our social and physical well-being and environmental quality, but it is not clear how well we understand these consequences. Problems in understanding these consequences are compounded by the fact that often those who benefit from a particular aspect of industrial production, transportation, or consumption are not the same as those who bear the costs. Some

resources, such as environmental quality, are seen as free, so that individuals or organizations may feel that they have paid the fair market price for a good or service even when some costs (e.g. loss of livelihood or habitat, degradation of environment, or clean-up costs) are borne by others. The environmental movement has raised awareness that our modes of production and transportation have costs, but has focused on individual actions to reduce our own contribution to environmental problems. However, we may remain poor judges of our own share of the risks (Buttel 1987) in terms of the quality of the physical environment surrounding our homes.

A growing literature connects collective decisions about how to organize our material lives with consequences for groups within the collective. In the US, a large emphasis has been placed on the role of residential racial segregation in contributing to differential health risks, resulting in health disparities. Blacks, as well as groups with lower education and income display worse health as measured by most outcomes, and residential neighborhood can account for considerable portions of these gaps (Do, 2008; K. King, Morenoff, & House, 2009; Morenoff, House, Hansen, Williams, Kaplan, & Hunte, 2008). The current puzzle in the literature on neighborhoods in health disparities is in identifying mechanisms by which precise features of locales affect physical health. These mechanisms are likely to follow both overtly physical and also psychosocial (Daniels, Kennedy, & Kawachi, 2000; Wilkinson, 1996) mechanisms.

Racial variations in exposure to air pollution risk have been documented. Morello-Frosch and Jesdale (2006) found that at every income level, metropolitan African-Americans, Hispanic and Asians/Pacific Islanders were nearly twice as likely as whites to have elevated lifetime cancer risk as estimated by exposure to ambient air carcinogens. In a study of Maryland residents (Alperberg et al. 2005), census tracts in the lowest income quartile were 100 times more likely to be at high risk for cancer associated with air pollution. Likewise, in greater

Houston (Linder, Marko, & Sexton, 2008), it was generally the case that locations at higher risk contained more Hispanic and socially disadvantaged people, although some industrial activity created a more complicated picture. It is generally known that air pollution levels have been documented to relate to health risks, but the extent to which air pollution variation is responsible for health risk disparities is less clear, given that much of this research on health risk uses models of risk based on pollution rather than observed measures of population health.

The literature discussing how these health risk disparities come to occur tends to assume that residents of communities can evaluate and respond to their risk, for instance by moving away from perceived risk sources, a practice considered to change land values, resulting in assortment of individuals with the least resources into areas with higher risks. But most of this evaluation process takes place in the absence of concrete evidence about risks. For instance, NIMBY (“not in my backyard”) movements to oppose installation of industrial facilities usually take place while a facility is only in the planning stages, when the potential risk for residents is likely not known. Many forms of air pollution may be invisible and not detectable by smell, and the most visible or noxious fumes may not be the most hazardous. Sometimes a possible risk may be observable (e.g. a “cancer cluster”) but cannot be traced to any clear source. Actual health risks of even the most widely discussed chemicals are disputed, and many risks may not yet have been discovered by scientists. Even when scientifically derived data exist, methodology is complex so that, for instance, the EPA recommends against use of National Air Toxics Assessment for prediction of tract-level health risks (EPA – documentation for 2002 NATA data). Although it is possible for individuals to access this data (for instance by using scorecard.org), it is likely that few do so, and that those who do access this objective data are relatively well-educated. Given this lacuna in lay or scientific objective knowledge about air

pollution, then, individual, institutional, or collective action on the basis of air pollution risk is, at least to a large extent, based on perceived rather than objective risk.

The present study seeks to evaluate the sources of perception of air quality by evaluating correlations of perceived air quality sociodemographic, psychosocial, built environment, and objective air pollution data.

Data

The measure of perceived air quality and sociodemographic and psychosocial measures, along with information on residential location come from the Chicago Community Adult Health Study (CCAHS). The CCAHS is a multi-level study of the impact of individual, social, and built environmental factors on health and how they contribute to socioeconomic and racial-ethnic disparities in health. This probability sample of 3105 adults age 18 and older in the city of Chicago, has a response rate of 71.8%. The sample is drawn from the 343 neighborhood clusters (NCs) of contiguous tracts covering the entire city of Chicago, developed and characterized by the Project on Human Development in Chicago Neighborhoods (PHDCN) (<http://phdcn.harvard.edu/>), with up to 21 respondents per NC. Because this is a representative sample, analyses can be weighted to represent the adult population of Chicago for 2000.

Perceived Air Quality

Respondents indicated their assessment of the air quality in their neighborhood on a four point scale from 1 to 4, including “Excellent,” “Good,” “Fair,” and “Poor.” For ease of analysis, the four categories are recoded into a dichotomous variable in which “Fair” and “Poor” are

coded as 1 and “Excellent” and “Good” are coded as 0. Thus, our models predict fair/poor as opposed to excellent/good perceived air quality.

Sociodemographics

Our sociodemographics are coded in a series of dummy variables. *Gender* is coded such that males are treated as the reference category. We use four race/ethnic categories: non-Hispanic whites (the reference), non-Hispanic blacks, Hispanics, and other non-Hispanics. Dichotomous variables represent different age groups (30-39, 40-49, 50-59, 60-69, and 70 years and over), with 18-29 as the reference group. Three dichotomous categorical variables measure years of *education*, 0-11, 12-15, and 16+. Household income is also represented by dichotomous indicators of income less than \$5,000, \$15,000-\$39,000, \$40,000 or more, and missing income, with \$5,000-\$15,000 as the reference category.

Exposure to Neighborhood Air

We also examine a set of potential sociodemographic moderators which we believe may affect the exposure to a negative experience with air quality. Dichotomous indicators represent the presence of minor child in the household, and whether someone in the household owns a car. Finally, we control for how many days per week the respondent reports walking, including a dummy variable for walking once or less per week.

Personality

Cynical people may be more likely to report lower air quality at a constant level of actual pollution. Our cynical hostility measure results from a principal components factor analysis of

five items from the Cook-Medley Hostility Scale. Each respondent was asked whether: “Most people inwardly dislike putting themselves out to help other people,” “Most people will use somewhat unfair means to gain profit or an advantage rather than lose it,” “No one cares much what happens to you,” “I think most people would lie in order to get ahead,” and “I commonly wonder what hidden reasons another person may have for doing something nice for me.” These questions, which tap into an antagonistic mistrust about other people’s motivations, were coded on a four-point scale from strongly disagree to strongly agree.

Systematic Social Observation

One component of the CCAHS was to send trained raters into neighborhoods to assess ecological conditions using criteria which were more standard than those used by respondents. SSO measures perform well in comparison with other datasets (Bader, Ailshire, Morenoff, & House, 2010; Clarke, Ailshire, Melendez, & Bader, 2010; K. E. King & Ailshire, 2010), although it has been suggested that they perform less well when single observations are used to observe phenomena which vary by season and time of day (Schaefer-McDaniel, Caughy, O’Campo, & Gearey, 2010), such as air quality, noise, and traffic volume. Of relevance for air quality, CCAHS SSO trained raters assessed the area around respondents’ homes for noxious smells and traffic volume.

Neighborhood Socioeconomic Measures

We use neighborhood socioeconomic data at the tract level. Using factor analysis, Morenoff and colleagues (Morenoff et al., 2008) developed four orthogonal (uncorrelated) factors to represent the social environment. The first factor, socioeconomic disadvantage,

includes low family incomes, high levels of poverty, public assistance, unemployment, female-headed families, never-married adults, and few owner-occupied homes. The second factor includes characteristics associated with neighborhood affluence (concentrations of people with high education and in professional/managerial occupations) and gentrification (a residentially mobile population consisting of young adults and few children under the age of 18). The third factor includes racial/ethnic/immigrant composition, (higher values indicate more Hispanic and foreign born and fewer non-Hispanic blacks). The fourth factor measures older age composition (especially people over 70 but also those between ages 50-69, and few young adults or people who have never married).

Density of Polluting Industrial Facilities

The Environmental Protection Agency maintains a yearly list of facilities who meet certain thresholds for the disposal or other release of listed toxic chemicals and their locations (U.S. Environmental Protection Agency, 2002). Being listed in the Toxics Release Inventory does not necessarily mean that a facility released toxics into the neighborhood, if releases occur they may not be hazardous to humans, and the quantity of toxics release may not match reports. TRI facilities are included here because living near an industrial facility may influence the individual's perception of the air quality in their neighborhood, and because TRI facility location is a commonly used proxy for risk in environmental health and justice research (Bolin, Nelson, Hackett, Pijawka, Smith, Sicotte et al., 2002; Dolinoy & Miranda, 2004; Mohai, Lantz, Morenoff, House, & Mero, 2009; Sicotte & Swanson, 2007). The present analyses consider the number of TRI facilities located within 1 km of the respondents geocoded home address.

Industrial and Transportation Land Use Proportion

Because the public may not draw a distinction between TRI and non-TRI facilities, and because non-TRI industrial facilities may also be air pollution sources, the analyses consider a measure of the proportion of land use in the surrounding 1 km which is industrial according to the Chicago Metropolitan Authority for Planning (CMAP, 2006; K. E. King & Ailshire, 2010). Transportation land use is also considered. Another concern is that the TRI facility toxics release may not occur at the reporting address used in geocoding. Figure 4 shows the locations of TRI facilities and industrial and transportation land uses according to CMAP. Geocoded TRI facility locations sometimes occurred in locations that were not industrial according to CMAP.

Total Respiratory, Neurological, and Cancer Risks

Data come from the 2002 National Air Toxics Assessment, performed by the Environmental Protection Agency. Figures 1, 2, and 3 are preliminary quartile maps of tract-level risks of respiratory, neurological, and cancer risks, respectively. Using a kriging technique available in Terraseer's Space-Time Information System (STIS) software, the spatial support of these tract-level estimates is transformed to the 1 km buffer around the respondent's home. All three forms of health risks are elevated downtown, while respiratory and cancer risks trace the patterns of Chicago's main highways and neurological and cancer risks are raised near the East Side.

Preliminary Results

When aggregated to the neighborhood cluster level (to maintain anonymity) and mapped (Figure 5), perceptions of air quality appear at first glance to be related to industrial land use, and to a lesser extent, major streets.

Preliminary results of the logit regression on perceived fair/poor air quality are shown in Table 1. Variables may differ from those discussed in this proposal because the choice and specification of variables is currently under consideration. In particular, I am moving from a multilevel framework to a single-level framework with 1 km buffers because there is no evidence for the spatial scale of air quality perception. Unlike social processes, air pollution has little relationship with geographic barriers/boundaries on the ground. I chose 1 km because results for a project in progress suggest that the industrial and transportation land uses become highly prevalent at the 1 km scale in Chicago. I also have quite a bit of additional data on pollution and built environment characteristics which I may include, provided I can maintain a coherent narrative. In particular, I would like to consider resources such as parks and trees.

The results shown are consistent with the view that because women tend to report more concern about the environment (Mohai, 1997), they may also report higher levels of air pollution, but this ethic of care does not show up for all people in households with children present. Large racial disparities exist, mostly attributable to location, but some persist after controlling for neighborhood. This is expected, since minorities may have worse locations within neighborhoods, but also could be due to internalized racism in the form of expecting air quality to be lower. I could partially test this by adding cynicism alone to model 1. Cynicism increases, while low exposure decreases probability of perceiving fair/poor air quality.

Relative risk based on NATA data predicts perception of worse air quality, but only for cancer and neurological risks. I should consider why this may be. Noxious smells strongly

predict fair/poor perceived air quality, while traffic volume is a less robust predictor. In results not shown, TRI facilities also predict perception. The number of TRI facilities is highly skewed, with a large proportion of respondents near no facility, but many within 1 km of up to 16 facilities.

Tables and Figures

Table 1 – Preliminary Regressions on Perceived Fair/Poor Air Quality

Weighted Regressions on Perceived Fair/Poor Air Quality (n=2,983)

	OLS		HLM									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	
Female	b	b	b	b	b	b	b	b	b	b	b	
Race (ref=non-hisp White)	0.21 *	0.24 *	0.22 *	0.23 *	0.25 *	0.26 *	0.22 *	0.22 *	0.22 *	0.26 *	0.26 *	
Non-Hisp Black	0.58 ***	0.39 **	0.31 *	-0.09	0.39 **	-0.04	0.31 *	0.31 *	0.25 +	-0.05	-0.07	
Hispanic	0.46 ***	0.40 **	0.29 +	0.14	0.31 *	0.14	0.27 +	0.29 +	0.26 +	0.13	0.12	
Non-Hisp Other	-0.24	-0.35	-0.44	-0.45	-0.47	-0.44	-0.48	-0.45	-0.45	-0.44	-0.45	
Age (ref= 18-29)												
30-39	-0.05	-0.03	-0.02	-0.03	0.00	-0.05	-0.01	-0.02	-0.03	-0.06	-0.06	
40-49	0.11	0.12	0.14	0.16	0.16	0.13	0.16	0.14	0.14	0.13	0.14	
50-59	-0.20	-0.18	-0.20	-0.17	-0.17	-0.19	-0.17	-0.19	-0.20	-0.20	-0.19	
60-69	-0.26	-0.14	-0.14	-0.10	-0.08	-0.10	-0.12	-0.14	-0.12	-0.09	-0.10	
70+	-0.42 *	-0.21	-0.16	-0.13	-0.11	-0.14	-0.12	-0.15	-0.16	-0.14	-0.13	
Education (ref=0-11 years)												
12 Years	-0.41 ***	-0.30 *	-0.25 *	-0.18	-0.25 *	-0.19	-0.23 *	-0.25 *	-0.23 *	-0.18	-0.18	
13+ Years	-0.53 ***	-0.34 *	-0.29 +	-0.17	-0.38 *	-0.18	-0.29 +	-0.29 +	-0.29 +	-0.19	-0.18	
Income (ref=\$5,000-14,999)												
\$0-4,900	-0.17	-0.20	-0.22	-0.18	-0.19	-0.19	-0.19	-0.22	-0.21	-0.19	-0.19	
\$15,000-39,999	-0.08	0.01	0.00	0.06	0.02	0.05	0.01	0.00	0.03	0.06	0.06	
\$40,000+	-0.25 +	-0.06	-0.05	0.07	-0.05	0.05	-0.03	-0.05	-0.02	0.06	0.06	
Inc. Missing	-0.13	-0.06	-0.04	0.05	0.01	0.04	-0.01	-0.04	0.02	0.06	0.06	
Interaction with Environment												
HH owns car	-0.35 **		-0.30 **	-0.27 **	-0.27 **	-0.27 *	-0.28 **	-0.30 **	-0.29 **	-0.27 *	-0.26 *	
Walk <= 1/week	-0.35 **		-0.31 *	-0.29 *	-0.28 *	-0.26 *	-0.30 *	-0.31 *	-0.31 *	-0.27 *	-0.27 *	
Minor present	0.09		0.11	0.08	0.16	0.09	0.12	0.11	0.13	0.09	0.09	
Hostility	0.46 ***		0.42 ***	0.41 ***	0.43 ***	0.41 ***	0.42 ***	0.42 ***	0.42 ***	0.41 ***	0.40 ***	
Orthogonal Factors												
Disadvantage			0.36 ***			0.32 ***				0.28 ***	0.27 ***	
Affluence			-0.20 *			-0.35 ***				-0.35 ***	-0.36 ***	
Hisp. FB			-0.08			-0.12				-0.12	-0.13	
Older Age Structure			-0.14 *			-0.05				-0.05	-0.03	
Standardized EPA NATA Estimates of Risk												
Total Neurological Risk					0.16 +	0.22 **				0.22 **	0.22 **	
Total Cancer Risk					0.24 **	0.17 **				0.17 **	0.17 *	
Total Respiratory Risk					-0.04	0.07				0.06	0.06	
Standardized SSO Measures												
Volume of Traffic							0.14 *			0.05		
Heavy Traffic							0.03					
Noxious Smells								0.23 ***	0.11 +	0.11 +	0.11 +	
Constant	-0.42 *	-1.51 ***	-1.45 ***	-1.30 ***	-1.61 ***	-1.34 ***	-1.50 ***	-1.46 ***	-1.47 ***	-1.34 ***	-1.33 ***	

Figure 1 – Total Respiratory Risk

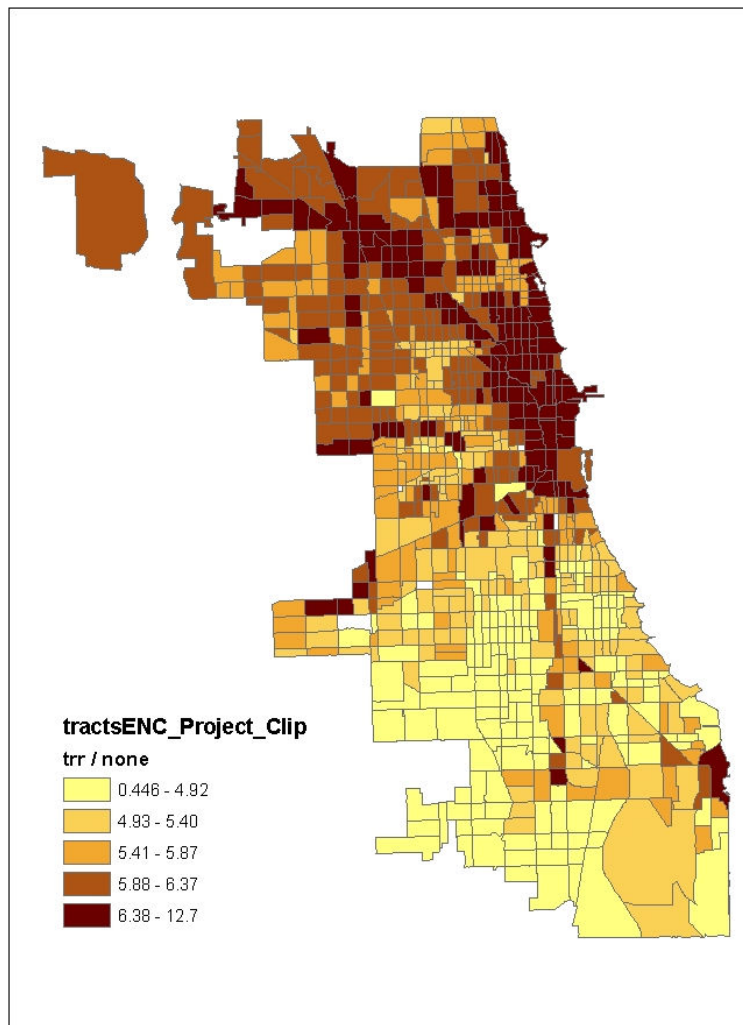


Figure 2 – Total Neurological Risk

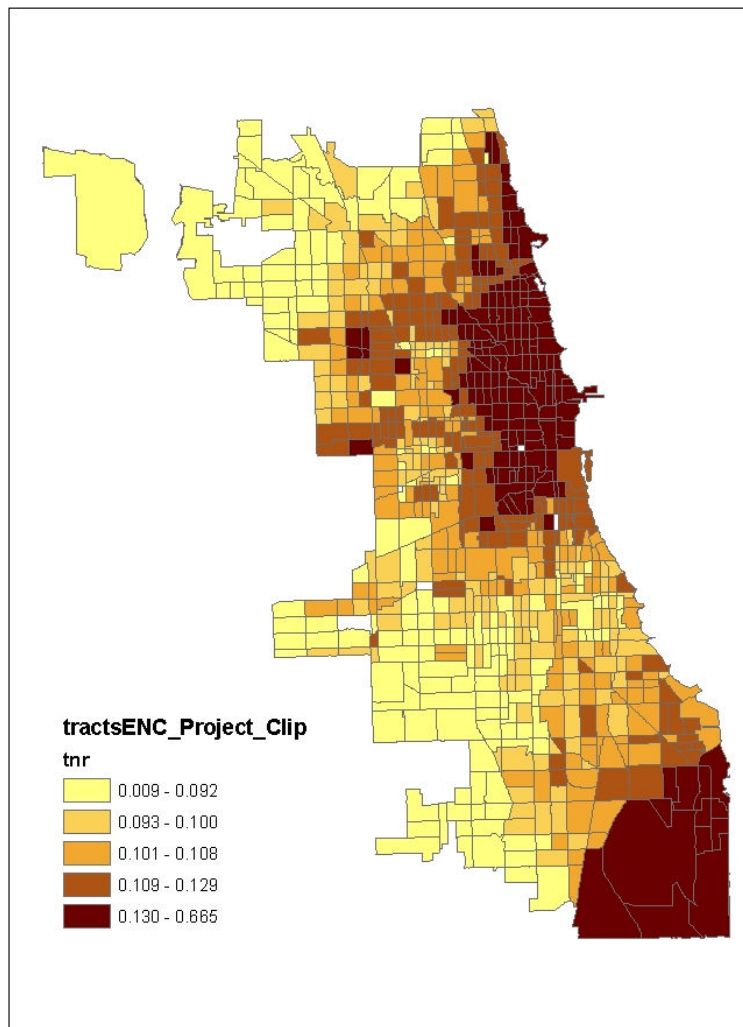


Figure 3 – Total Cancer Risk

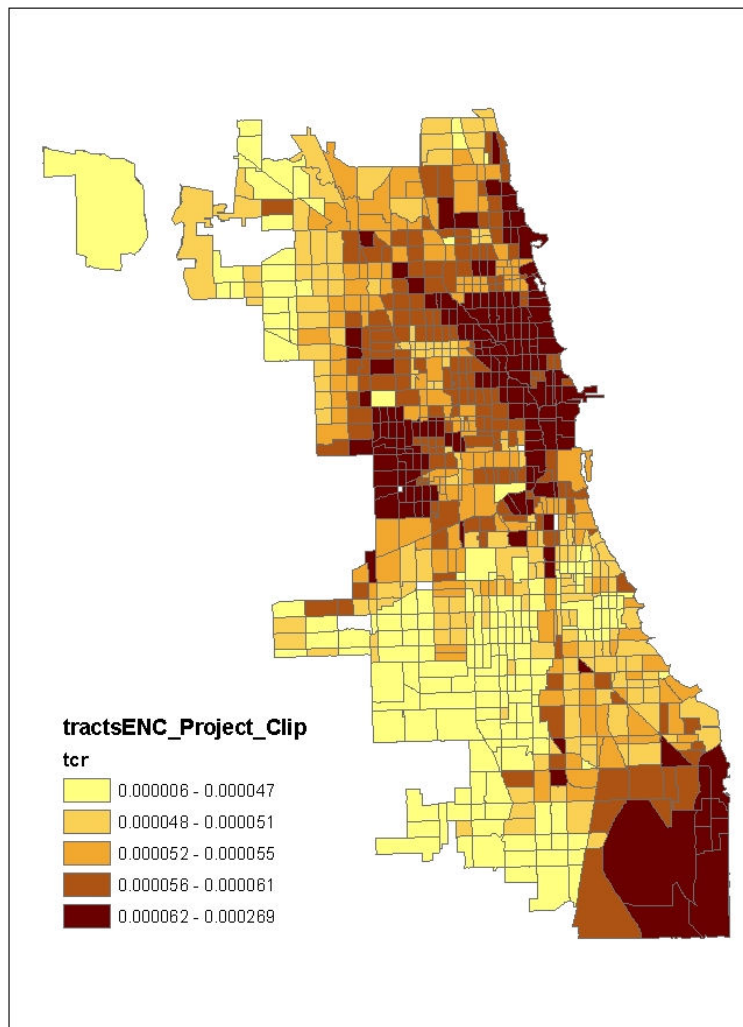


Figure 4 – Industrial and Transportation Land Uses (2001) in Chicago and Toxic Release Inventory Industrial Facilities within 4 km of Chicago (2002)

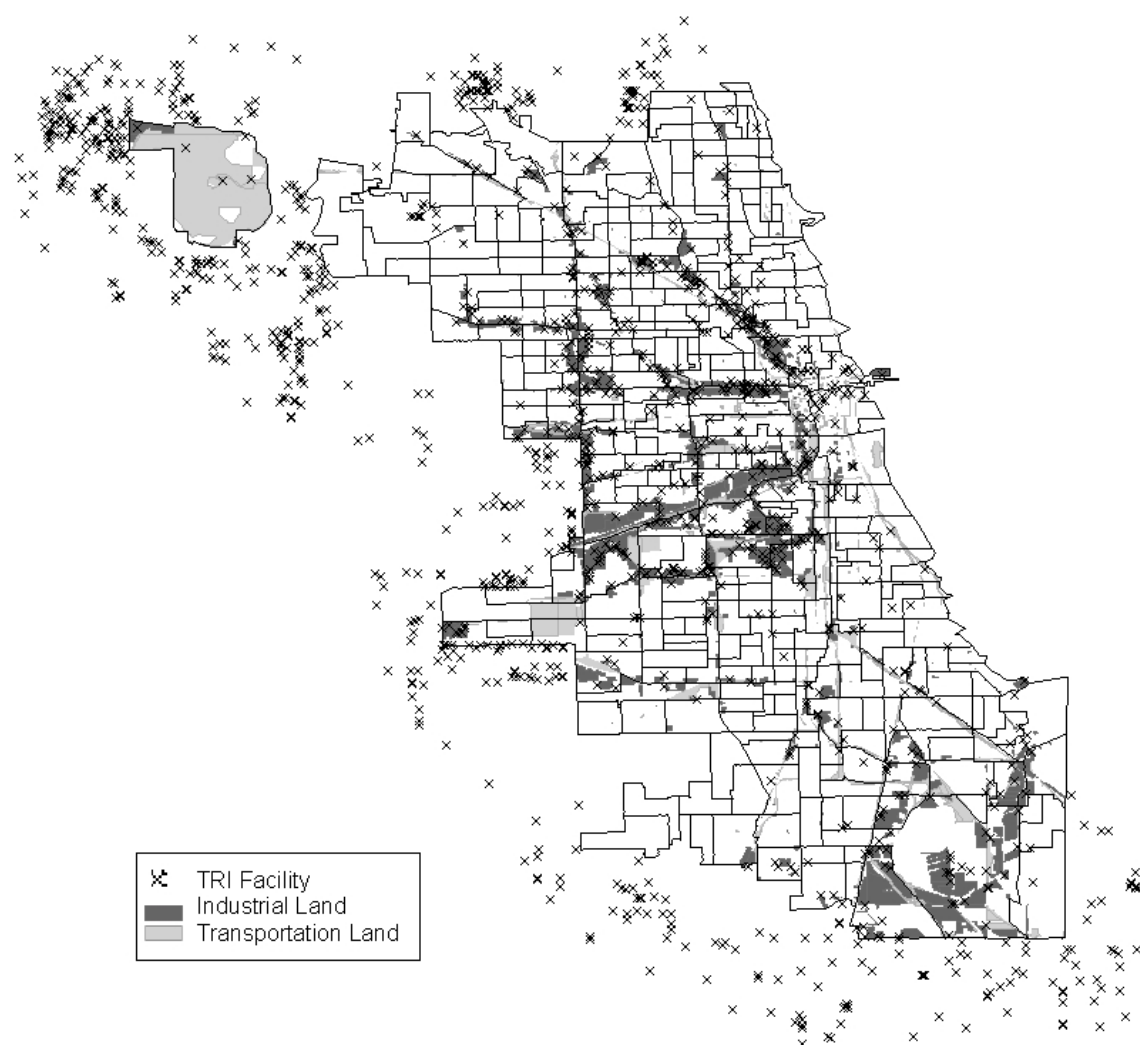
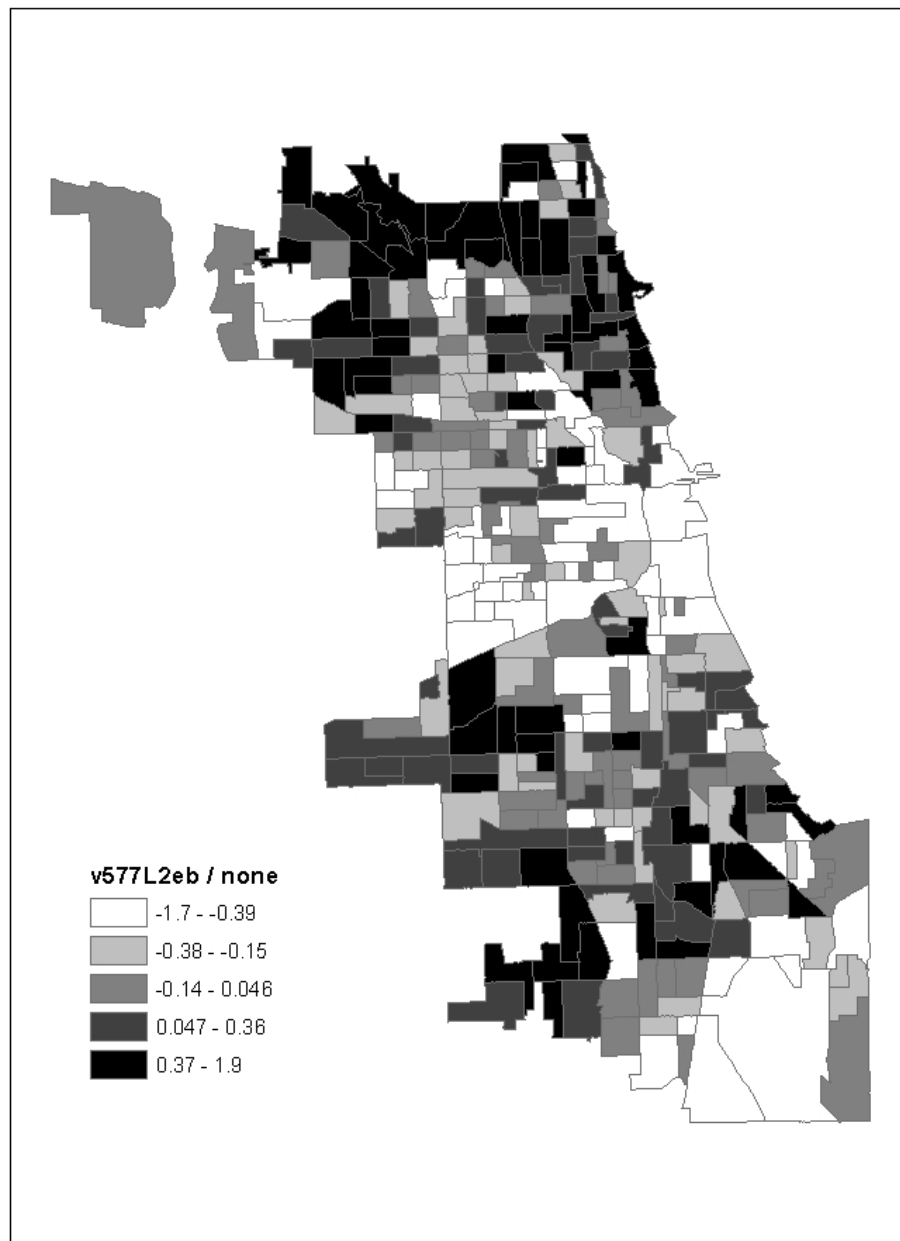


Figure 5 – Perceived Air Quality, Aggregated to NC-level, CCAHS 2001-3
(*darker colors indicate better air*)



Works Cited

- Bader, M. D. M., Ailshire, J. A., Morenoff, J. D., & House, J. S. (2010). Measurement of the local food environment: A comparison of existing data sources. *American Journal of Epidemiology*.
- Bolin, B., Nelson, A., Hackett, E., Pijawka, K. D., Smith, C. S., Sicotte, D., et al. (2002). The Ecology of Technological Risk in a Sunbelt City. *Environment and Planning A*, 34, 317–339.
- Clarke, P., Ailshire, J., Melendez, R., & Bader, M. (2010). Using Google Earth to Conduct a Neighborhood Audit: Reliability of a Virtual Audit Instrument.
- CMAP. (2006). Data Bulletin: 2001 Land-use Inventory for Northeastern Illinois. Chicago Metropolitan Agency for Planning
- Daniels, N., Kennedy, B., & Kawachi, I. (2000). *Is Inequality Bad for our Health?*: Beacon Press.
- Do, D. P., Brian Karl Finch, Ricardo Basurto-Davila, Chloe Bird, Jose Escarce, Nicole Lurie (2008). Does place explain racial health disparities? Quantifying the contribution of residential context to the Black/white health gap in the United States. *Social Science & Medicine*, 67, 1258-1268.
- Dolinoy, D. C., & Miranda, M. L. (2004). GIS Modeling of Air Toxics Releases from TRI-Reporting and Non-TRI-Reporting Facilities: Impacts for Environmental Justice. *Environmental Health Perspectives*, 112(17), 1717–1724.
- King, K., Morenoff, J. D., & House, J. S. (2009). Cumulative Biological Risk Factors: Neighborhood Socioeconomic Characteristics and Race/Ethnic Disparities Population Studies Center. Ann Arbor: University of Michigan.
- King, K. E., & Ailshire, J. A. (2010). Comparison of Systematic Social Observation and Aerial Photography Data on Land Use in Chicago. Population Studies Center. Ann Arbor, MI.
- Linder, S., Marko, D., & Sexton, K. (2008). Cumulative cancer risk from air pollution in Houston: disparities in risk burden and social disadvantage. *Environmental Science Technology*, 42(12), 4312-4322.
- Mohai, P. (1997). Gender Differences in the Perception of Most Important Environmental Problems. *Race, Gender, and Class*, 5(1), 153.
- Mohai, P., Lantz, P. M., Morenoff, J., House, J. S., & Mero, R. P. (2009). Racial and Socioeconomic Disparities in Residential Proximity to Polluting Industrial Facilities: Evidence From the Americans' Changing Lives Study. *American Journal of Public Health*, 99(S3), S649-S656.
- Morello-Frosch, R., & Jesdale, B. (2006). Separate and unequal: residential segregation and estimated cancer risks associated with ambient air toxics in U.S. metropolitan areas. *Environmental Health Perspectives*, 114(3), 386-393.
- Morenoff, J. D., House, J. S., Hansen, B. B., Williams, D., Kaplan, G., & Hunte, H. (2008). Understanding social disparities in hypertension prevalence, awareness, treatment, and control: The role of neighborhood context. *Social Science & Medicine*, 65, 1853-1866.
- Schaefer-McDaniel, N., Caughy, M. O. B., O'Campo, P., & Gearey, W. (2010). Examining methodological details of neighbourhood observations and the relationship to health: A literature review. *Social Science & Medicine*, 70, 277–292.
- Sicotte, D., & Swanson, S. (2007). Whose Risk in Philadelphia? Proximity to Unequally Hazardous Industrial Facilities. *Social Science Quarterly*, 88(2), 515–534.
- U.S. Environmental Protection Agency. (2002). Toxics Release Inventory. <http://www.epa.gov/tri/>.
- Wilkinson, R. G. (1996). *Unhealthy societies: The afflictions of inequality*. New York: Routledge.