Urban Institute

Indianapolis Site-Specific Neighborhood Health Analysis: Environmental Factors and Risk of Childhood Obesity

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EXECUTIVE SUMMARY

Goals and Hypotheses

Research suggests that environmental factors likely account for the dramatic increase in obesity over the past ten years. This analysis examines environmental factors relating to socioeconomic status or physical activity that may mediate obesity risk independent of individual-level factors, such as race, gender, and age.

The hypotheses for the Indianapolis analysis are:

1. *Children living in areas of lower socioeconomic status (as measured by income and educational attainment) are more likely to be obese than other children.*

2. *Children living near opportunities for exercise (specifically parks, greenways, after-school programs, and YMCAs) are less likely to be obese than other children.*

3. *Children living in areas with high exposure to social barriers (as measured by high crime rates, single parent families and those who are linguistically isolated) are more likely to be obese.*

Data

Individual (Patient)-level Indicators

Age (4-18years)
Race (Caucasian, African American, Latino, Other)
Gender (Male, Female)
Body Mass Index (BMI)

Socioeconomic Indicators

% of population age 25 and older without a high school degree
Median Household Income
Median Family Income

Physical Activity Opportunity Indicators

Distance to nearest YMCA
Distance to nearest City Park
Distance to nearest Greenway
Distance to nearest After-School Program with physical education curricular components

Barriers to Exercise Indicators

% of families that are single-parent
% of households that are linguistically isolated
Violent crime rate (per square mile)

Findings and Implications

Findings are presented in two phases: I. Analysis by census tract and II. Analysis by census block group.

Phase I: Analysis of data at Census tract-level

Approach

We obtained patient-level data from an archived, searchable electronic medical record. Our inclusion criteria specified children who were seen in Indiana University Medical Group Pediatric Clinics during the calendar year 2000 and had simultaneously recorded height and weight measurements.

We obtained social environmental data from a local community information system.

We used patient height and weight measurements to derive body mass index (BMI); BMI was used to categorize patients as normal weight (BMI <=25), overweight (BMI > 25 & <= 30), or obese (BMI > 30).[1, 2] Children's addresses were geocoded to identify their census tract of residence. For each independent environmental variable, we conducted bivariate analysis to examine associations with obesity. Variables demonstrating a significant association were subsequently included in multivariate regression models.

Findings

- Individual-level factors:
  - Females are more likely to be obese than males.
  - Older children are more likely to be obese than younger children.
  - There is an interaction between gender and age such that older females are the most likely to be obese.
  - African Americans are more likely to be obese than Caucasians or other races.
- Socioeconomic factors:
  - Children living in areas of lower income are more likely to be obese than other children. For each $10,000 increase in median household income, the odds of obesity decrease by 11%.
  - Educational attainment in census tracts is not significantly predictive of childhood obesity.
- Opportunities for exercise:
  - Proximity to the nearest play space (specifically parks, greenways, after-school programs, and YMCAs) is not significantly predictive of obesity.
- Social barriers:
  - Both crime and single parenting are significantly associated with obesity in bivariate analyses; but when median income was included in a multivariate model as a covariate, neither crime nor single parenting is significantly predictive of obesity.

Phase II: Analysis of data at Census block group-level

Approach

We obtained patient-level data from an archived, searchable electronic medical record. Our inclusion criteria specified children who were seen in Indiana University Medical Group Pediatric Clinics during the calendar years 1996-2000 and had simultaneously recorded height and weight measurements.

We obtained social environmental data from a local community information system.

We used patient height and weight measurements to derive body mass index (BMI); BMI was used to categorize patients as normal weight (BMI < 85% age-adjusted norms for American children, based on growth charts from the CDC), overweight (BMI ≥ 85% & < 95% age-adjusted norms), or obese (BMI ≥ 95% age-adjusted norms).[3, 4] Children's addresses were geocoded to identify their census block group of residence. For each independent variable, we conducted bivariate analysis to examine associations with obesity. Variables demonstrating a significant association were subsequently included in multivariate regression models.

Findings

- Individual-level factors:
  - Females are more likely to be obese than males.
  - Older children are more likely to be obese than younger children.
  - Hispanics, as a race category, are most likely to be obese.
  - African Americans are more likely to be obese than Caucasians.
  - There is no interaction between gender and age.
  - There is an interaction between gender and race. Hispanic females are the most likely to be obese.
- Socioeconomic factors:
  - Children from areas with very low median income are the most likely to be obese; the odds of obesity relative to children from areas with upper income are 1.55 (95% confidence interval: 1.27-1.90)
- Opportunities for exercise:
  - Not analyzed in this phase.
- Social barriers:
  - Crime is not significantly predictive of obesity.
  - Single parenting is not significantly predictive of obesity.
  - Linguistic isolation is not significantly predictive of obesity.

- Map Review:

  A review of the spatial distribution of obese patients against environmental and individual-level variables revealed:
  - There is no readily discernable spatial pattern in the distribution of obese patients in Marion County (see Map 3 in Appendix B).
  - The distribution of race for all patients follows the distribution of race for the general populace of Marion County (see Map 4 in Appendix B).

- There is no readily discernable association between the spatial pattern of obese patients and the spatial pattern of any of the socioeconomic factors included in this analysis (see Maps 5 - 9 in Appendix B).

Conclusions

- Low environmental socioeconomic status (as measured by income) is a risk factor for obesity.
- Obesity is more prevalent in minority populations.
- Analyses at the census tract and block group-levels produce various results, so the best geographic level for analysis is yet to be determined.

Recommendations

- Educational efforts may be an especially effective means for preventing obesity; based on the findings in this study, these educational programs should be targeted toward African American and Latino populations. Schools will make good partners for designing and implementing the educational programs. Programs should involve families.
- Educational attainment data should be collected more frequently.

Future Research

- Explore alternate ways to measure and analyze factors that influence diet, such as fast food density and proximity to grocery stores.
- Explore alternate ways to measure and analyze factors that influence physical activity, such as the "built" environment (e.g. subdivision layouts, sidewalks, and transportation networks).
- Explore additional individual-level factors as predictors of obesity, such as insurance status.
- Explore alternate analysis methodology incorporating more sophisticated spatial analysis techniques such as geostatistical analysis.
- Conduct year-by-year analysis of patient data and social environmental factors. (This study applied one year of environmental variables to 5 years of patient data. Recommend in the future trying to collect social environmental variables for each year.)
- Continue the analysis with the full complement of environmental variables from the conceptual model (Figure 1).

Abbreviations

BMI – Body Mass Index; GIS – Geographic Information System; MSA – Metropolitan Service Area; RMRS – Regenstrief Medical Record System; SAVI – Social Assets and Vulnerabilities Indicators Project; SES – Socioeconomic Status

BACKGROUND

Burden Of Disease

In the past two decades, the prevalence of obesity has risen so dramatically worldwide that many investigators have suggested the onset of a global obesity epidemic.[5] According to the classification scheme devised by the World Health Organization, 54% of U.S. adults are overweight [a body mass index (BMI) >= 25 kg/m^2] and 22% are obese (BMI >= 30 kg/m^2).[6] The prevalence of overweight in U.S. children is estimated between 22 and 30%, representing a doubling since 1980.[7, 8]

In 2000, the Centers for Disease Control and Prevention found that 21% of Indiana adults were considered obese and 35% were overweight, making Indiana the 12th fattest state in the U.S. Seventy-eight percent of Indiana citizens get less than the daily-recommended amount of physical activity; 25% of Indiana citizens are not physically active at all. According to a Medicaid analysis reported by the Indiana Family and Social Services Administration, the estimated cost to Indiana taxpayers to treat obesity-related illnesses in 1998 was $233 million, an average of $3,188 per person.

Concern about the increasing prevalence of childhood obesity centers on its link to increased adult health risks that translate into increased medical care and disability costs. In the U.S., the total cost attributable to obesity exceeded $100 billion in 2000, or approximately 8% of the national health care budget[9] with $52 billion in direct medical costs resulting from diseases associated with obesity.[10-12] Although the immediate health implications of obesity in childhood have not been examined extensively, obese children are likely to become obese adults, particularly if obesity is present during adolescence.[13, 14] Adverse social and psychological effects of childhood obesity have been demonstrated.[15, 16] Overweight during adolescence has been shown to have deleterious effects on high school performance, educational attainment, psychosocial functioning, and socioeconomic attainment.[12]

Overweight is associated with various cardiovascular disease risk factors even among children as young as 7 years of age.[17] Longitudinal data have shown that overweight, hypertension, and dyslipidemia were associated with these same risk factors in childhood. A growing body of epidemiological evidence supports the theory that obesity related disease begins at a young age, and that risk factors for disease persist or track with advancing age, growth, and development.[18]

Because obesity is highly prevalent in both children and adults, its onset is insidious, and the expression of primary risk factors for obesity-related disease burden occurs at young ages, there is a clear rationale to presume health promotion and the primary prevention of obesity in childhood should reduce the adult incidence of cardiovascular disease.[19-22] Moreover, overwhelming difficulty has been encountered when intervening to assist adults to lose weight and this further highlights the need for primary obesity prevention in childhood.

Environmental Approaches To The Prevention Of Obesity

Most adult obesity interventions are ineffective, with one-third to two-thirds of the weight loss being regained in one year and almost all weight being regained in five years.[23] The overwhelming difficulty of intervening to assist adults to lose weight points to the need for primary obesity prevention.[19-22, 24, 25] Most of the attempts to prevent obesity have adopted educational approaches aimed at improving knowledge and motivation that in turn would presumably alter individual lifestyle choices.[26] Such approaches have been largely ineffective.[27] Redirecting approaches to target environmental factors that modify behavior may enable prevention to succeed because the approach does not exclusively rely on individual will.[26, 28]

The U.S. environment is becoming increasingly obesogenic. Americans are exposed to an unprecedented amount of energy dense, heavily advertised, inexpensive, and readily available food. Purchase of larger portion sizes is commonly marketed as a better value. Increasing numbers of working women may be contributing to greater frequency of restaurant meals, fast-foods meals, and convenience foods.[29] Numerous environmental factors also promote decreased energy expenditure. Despite the clearly documented health benefits of routine physical activity, approximately one-quarter of Americans remain completely inactive, and leisure time inactivity is up to 3-fold more common in lower-income populations.[30] Suburban communities often lack sidewalks and neighborhood layout often impedes walking even short distances to stores and recreation. Individuals in urban settings report reluctance to exercise outdoors because their neighborhoods are perceived as unsafe.[31, 32] Occupations are increasingly sedentary with the progressive adoption of automated equipment and electronic communication. Labor saving devices such as remote controls are also becoming more common in the home.

Children’s lifestyles are also becoming strikingly sedentary. Studies have documented that children watch an average of 28 hours of television per week and that the amount of television viewing was directly related to the likelihood of obesity.[33] In 1977, children aged 5 to 15 years walked or biked for 15.8% of all their trips; by 1995, children made only 9.9% of their trips by foot or bicycle.[34] Schools are decreasing the availability of daily physical education.[35] The World Health Organization has long recognized that obesogenic environment factors are driving rapid rises in obesity and it formally stated the importance of studying how the environment can be changed to prevent obesity in 1986.[36] However, environmental strategies and interventions remain relatively under-studied.

Numerous reports have repeatedly echoed a call for physical activity interventions that focus on environmental changes.[37-40] Hays and Clark suggest that an individual’s level of physical activity is a function of expectations of performance and outcomes associated with exercise.[41] These expectations are influenced by knowledge of the benefits of physical activity and perceptions of barriers to exercise, including environmental barriers, both of which are correlated with sociodemographic characteristics and health status. In related work, Clark has identified preferred exercise activities as well as both environmental and psychological factors that influence physical activity.[42] In his study, subpopulations of low-income African-American and White males and females all identified walking as a preferred activity. They reported environmental barriers such as weather that cannot be influenced by policy and factors such as the quality of sidewalks and the availability of transportation to exercise facilities that can be influenced through intervention.

Dietary interventions that focus on environmental change are in their infancy and merit additional testing. However, several studies offer compelling evidence that research and interventions are needed in this area. Evidence suggests that early educational messages can promote preferences in children for healthful foods.[43] However, any promotional messages about healthy diet are likely drowned given the finding that the average American child views as many as 10,000 food advertisements on television annually; 90-95% of these are for sugared cereals, fast food, soda, and candy.[44] Strong evidence links exposure to such advertising and child food preferences. In a separate study of predictors of food choice among adults at vending machines, it was shown that reduced pricing of healthy food options greatly increased the sale of these items.[45] Finally, some researchers have suggested that taxing unhealthy foods, for the purpose of subsidizing healthy foods, would synergistically act to improve overall dietary behavior.[46]

Spatial Analytic Methods and Geographic Information Systems: Use in Obesity Research and Epidemiology

Person, place, and time: these are the three basic categories of investigative content needed to develop strategies for managing the outbreak of obesity. The majority of epidemiologic effort to date has been focused on person and time; the need is for more attention towards questions concerning how "place" (i.e. physical and social environment) contributes to the etiology of obesity. Advancement in geographic information systems over the past 20 years now provides a powerful way to conduct multivariate spatial statistical modeling of obesity in terms of its changing prevalence and environmental risk factors.

Past methods for analyzing suspected environmental disease covariates depended largely on indirect or surrogate measures of observation.[47] For example, interview data on occupation in the ship building industry served as a surrogate for environmental exposure to asbestos.[48] Today, environmental data are routinely collected by a host of administrative agencies through direct continuous monitoring (e.g. air and water quality) as well as periodic survey (e.g. the U.S. Census). Digital satellite photography provides real-time and highly detailed digital representations of landscape and landcover that can be classified and statistically correlated with factors underlying disease processes such as host and vector habitats. GIS and satellite technology have long been used to study infectious disease.[49-52]

With increasingly rich and diverse data sets, GIS applications are rapidly expanding beyond the more traditional uses in surveillance of acute and infectious disease. With GIS, we are learning more about the associative environmental causes of childhood pedestrian and bicyclist injuries,[53, 54] elevated child lead exposures,[55] cancer[56, 57], child maltreatment,[58] elevated risks of low-birth weight,[59] and high infant mortality rates.[60] Finally, GIS, when combined with spatial analytic methods, has been found helpful in the study of health care and health care delivery. Examples of this type of study include identifying the most advantageous routings for emergency medical services[61] and examining disparities in health services between rural and urban areas.[62-65]

GOALS AND HYPOTHESIS

Research suggests that environmental factors likely account, in large part, for the dramatic increase in obesity over the past ten years. This analysis examines environmental factors relating to socioeconomic status or physical activity that may mediate obesity risk, independent of individual-level factors, such as race, gender, and age.

The hypotheses for the Indianapolis analysis are:

1. *Children living in areas of lower socioeconomic status (as measured by income and educational attainment) are more likely to be obese than other children.*

2. *Children living near opportunities for exercise (specifically parks, greenways, after-school programs, and YMCAs) are less likely to be obese than other children.*

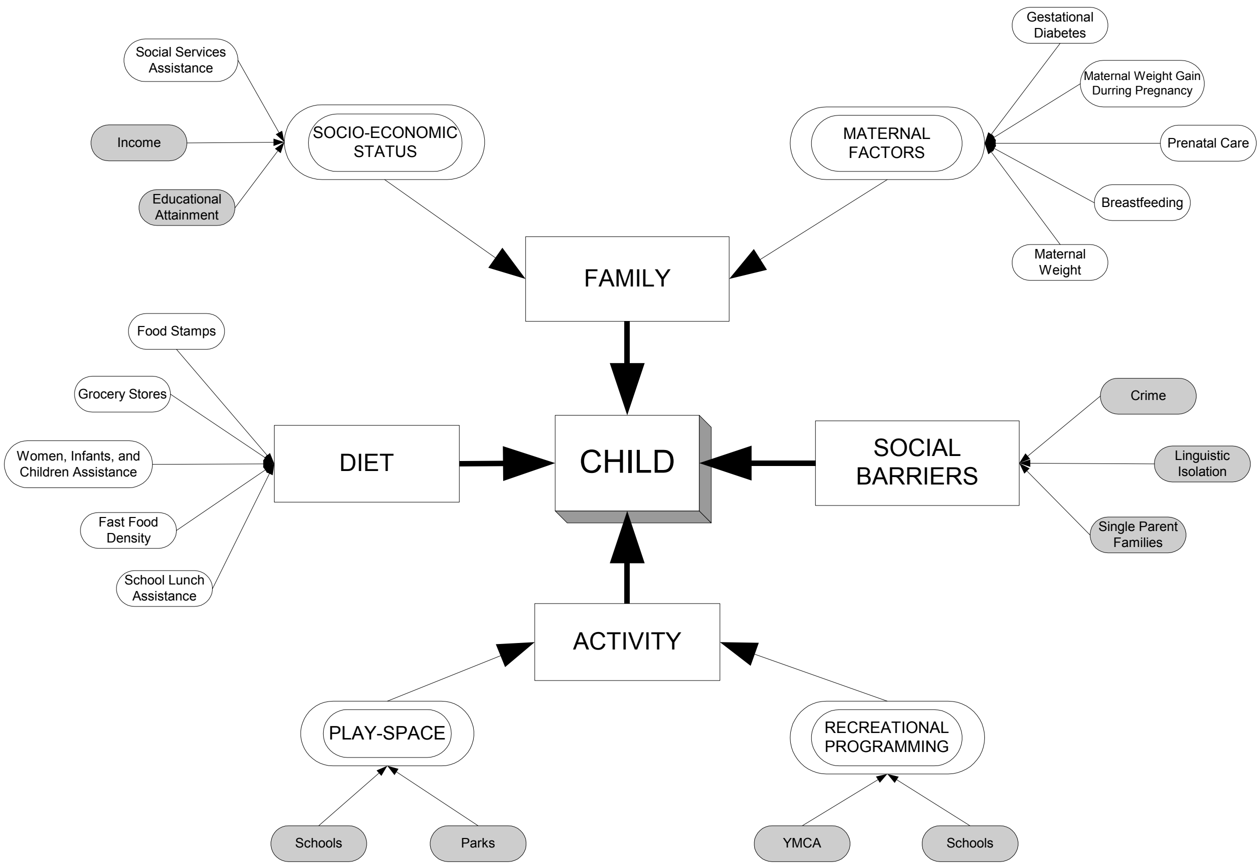
3. *Children living in areas with high exposure to social barriers (as measured by high crime rates, single parent families and those who are linguistically isolated) are more likely to be obese.*

APPROACH

Model Design

We have designed a preliminary conceptual model of physical and social environmental factors that may predict childhood obesity (Figure 1). These factors exert influence in four broad spheres: family, diet, activity, and social barriers. Measures of many of the factors are represented in the SAVI database, and we are still in the process of defining strategies to operationalize several of the other factors. The method of analysis is also in an exploratory phase. This study employs spatial analysis using GIS technology into health research methodology. For this preliminary study, we chose factors from the "Activity" sphere that are readily available in SAVI as a means for testing the spatial analysis approach to defining variables.

Figure 1. Conceptual Model of Environmental and Social Factors Predicting Childhood Obesity. Bubbles Containing Factors Included in this Analysis are Shaded.



Data Collection and Manipulation

This study examines the relationship of obesity to patient-level indicators, such as age and race; socioeconomic status indicators, such as income; physical activity opportunity indicators, such as proximity to play space; and social barriers to exercise, such as crime.

We collected patient data from a network of six urban primary care clinics (Indiana University Medical Group), and collected variables representing socioeconomic status, social barriers, and access to exercise opportunities from an extensive community information system, the Social Assets and Vulnerabilities Indicators system. GIS was used to manipulate the data spatially and convert it into a format that can be analyzed using a statistical software package.

We conducted the analysis in two phases. Phase I utilized census tract-level data and one year of patient records data. Phase II utilized census block group-level data and five years of patient records data. The data and process are documented in more detail below. See Appendix A for detailed information about the contents and original source of the data.

Individual (Patient)-level Indicators

The Regenstrief Medical Records System (RMRS) is an electronic version of the paper medical chart, which has been in existence since 1974. It has now captured and stored 200 million temporal observations for over 1.5 million patients. Because RMRS data are both archived and retrievable, investigators may use these data to perform retrospective and prospective research. In Phase I of the study, we queried the Regenstrief Medical Record System to identify all children between the ages of 4 and 18 years seen in a network of six urban primary care clinics (Indiana University Medical Group, IUMG) in Indianapolis, IN, in the calendar year 2000 that reside in Marion County, IN. We also extracted demographic information, including age, race, and gender, for all children meeting these case definition criteria. We examined a random sample of children drawn from this cohort and found no significant skew in the distributions of gender and age. We identified a subset of children that had a simultaneous height and weight measured. We calculated body mass index (BMI) and classified children as "normal" [BMI < 25 kg/m^2, n = 1,521], "overweight" [BMI >= 25 and <30 kg/m^2, n = 470], or "obese" [BMI >= 30 kg/m^2, n = 505].

We transferred the patient data obtained from the RMRS into the SAVI database by converting patient addresses into real-world coordinates using a GIS process called "geocoding." The census tract in which the patient is located was also attached to the patient record using GIS. The tract identifier was used to link the tract-level indicators (described below) to the patients. 7% of the patients were eliminated from the study because they did not successfully geocode, and 114 additional children were excluded from the analysis because either the race information was misspelled, unknown or not recorded in their medical record or their BMI was not logical, (less than 10 or greater than 77). This study includes 89% of all Marion County patients between the ages of 4-18 with height and weight information seen at IUMG clinics in the calendar year 2000 (n = 2,496).

In Phase II of the study, we queried the RMRS to identify all children with the same inclusion criteria but with an expanded date range -- 1996- 2000 (see Map 1 in Appendix B). Again, we examined a random sample of children drawn from this cohort and found no significant differences in the distributions of gender and age when compared to the general patient population. We included 23,088 children who had a simultaneous height and weight measured. If a child visited IUMG clinics multiple times during the 5-year period, we included only the most recent measurements. In this phase, we used a different classification for weight based on age-adjusted BMI percentiles produced by the Centers for Disease Control and Prevention. The final classifications are defined as "normal" [BMI percentiles < 85, n = 11,133], "overweight" [BMI percentiles ≥ 85 and < 95, n = 2,893], and "obese" [BMI percentiles ≥ 95%, n =2,845]. The patients were geocoded and assigned a census block group identifier. 17% of the patients were eliminated from the study due to unsuccessful geocoding, and 1,247 additional patients were eliminated from the study due to illogical BMI percentile or race information in the record. This study includes 77% of all IUMG patients age 4-18 (with height and weight measurements) residing in Marion County (n = 17,871). In the final model, the analysis excludes 7 patients because the median family income of the block group they live in had a value of $0.

Environmental Factors

We collected a majority of the environmental factors from The Social Assets and Vulnerabilities Indicators (SAVI) database. The SAVI project is one of the most sophisticated and extensive systems of its kind (http://www.savi.org). SAVI contains more than 20 gigabytes of social demographic and environmental data covering the nine-county Indianapolis MSA. Examples of SAVI data include school performance measures, US Census data, health indicators, crime statistics, and social services utilization. SAVI is maintained by the Polis Center at IUPUI, a multidisciplinary research center dedicated to addressing the challenges of community development in Indiana, in partnership with the United Way of Central Indiana.

Socioeconomic Indicators

In Phase I, we selected two1990 census tract-level indicators from the SAVI database to represent socioeconomic status: Median Household Income and the Percent of Persons 25 Years and Older without a High School Diploma. We collected Median Household Income, and treated income as a continuous variable at increments of $1,000.

In Phase II, we collected Year 2000 census block-level data. We used the same measure of educational attainment, and measured income using Median Family Income (MFI). MFI only reports income for related people and is more likely to include a larger subset of the population of interest (families *with* children). Furthermore, MFI is less likely to be diluted with single person households, which do not include children. The income indicator was calculated by dividing the MFI of the block group by the MFI of the Indianapolis Metropolitan Statistical Area ($55,191). We classified each block group into one of the following categories, which are based on the definitions used by the US Department of Housing and Urban Development:

Extremely Low < 30% MSA MFI
Very Low ≥ 30% and < 50% MSA MFI
Low ≥ 50% and < 80% MSA MFI
Moderate ≥ 80% and < 95% MSA MFI
Middle ≥ 95% and < 120% MSA MFI
Upper ≥ 120% MSA MFI.

Physical Activity Opportunity Indicators

We selected proximity to play space as the indicator to represent opportunities for exercise. We selected several play spaces from the SAVI database, including locations of Young Men's Christian Associations (YMCA), city parks, greenways, and after-school programs with physical education curricular components. We used GIS to calculate the distance from each patient's home to his/her nearest play space. This variable was only used in Phase I of the analysis.

Social Barriers To Exercise Indicators

In Phase I, we selected single parent families and crime indicators from the SAVI database. We measured single parent families using 1990 single parent families as a % of all families. We measured crime as 2000 total "Part 1" crimes, which include criminal homicide, robbery, aggravated assault, burglary, larceny, motor vehicle theft, and rape. Simple assaults, which are not Part 1 crimes but give a more complete picture of the total crime activity, are also included in this measure. The crime data are only reported for the Indianapolis Police Department service area, which does not cover the entire county (see Map 2 in Appendix B).

In Phase II, we added census data on linguistic isolation as an indicator. We measured single parent families the same as in Phase I using 2000 data. Crime was measured as 2000 "Part 1" crimes per square mile. Linguistic isolation was measured as percent of households that are linguistically isolated for the year 2000.

Data Analysis

We first looked at descriptive statistics to ensure the data are representative of the general patient population by age, race, and gender. Patient demographics such as race, age, and gender, as well as environmental variables of the patients' neighborhoods, defined here as the census tract or block group in which they live, were subjected to bivariate analyses. We conducted multivariate logistic regression analysis using only those variables with significant association in bivariate analyses. Using the final model, we calculated the odds ratios for obesity across various segments of the population based on the variables in the model.

RESULTS

The results section consists of two main parts that represent the chronologic phases of our project. First, we present the results of an analysis where the unit of the analysis is <u>census tract</u> and the study cohort represents <u>patient encounters from year 2000</u>. Second, we present the results of analysis where the unit of the analysis is <u>census block group</u> and the study cohort represents <u>patient encounters from years 1996 through 2001</u>. Within each of the two main parts individual (patient)-level demographics are discussed, followed by results relating to the study hypotheses:

1. *Children living in areas of lower socioeconomic status (as measured by income and educational attainment) are more likely to be obese than other children.*

2. *Children living near opportunities for exercise (specifically parks, greenways, after-school programs, and YMCAs) are less likely to be obese than other children.*

3. *Children living in areas with high exposure to social barriers (as measured by high crime rates, single parent families and those who are linguistically isolated) are more likely to be obese.*

Phase I: Census Tract-Level Analysis

Individual (Patient)-Level Demographics

In the study population consisting of only patients who were measured in the year 2000 (Table 1), the estimated prevalence of childhood obesity is 20% and overweight is 19%. African Americans have slightly higher prevalence of obesity than Caucasians or other racial groups. The prevalence of obesity is substantially higher in females than in males (Figures 2 and 3). The rates of obesity differ greatly across the six groups formed by race and gender. African American girls have the highest rate of obesity while the boys in the "Other" category of race have the lowest rate of obesity.

Table 1. Distribution of BMI by Race and Gender for Year 2000 Study Cohort

	Black (%)	*White (%)*	*Other (%)*
Male			
Normal	391 (69)	242 (66)	46 (65)
Overweight	85 (15)	69 (18)	16 (23)
Obese	93 (16)	64 (17)	9 (13)
Female			
Normal	495 (55)	306 (61)	41 (56)
Overweight	184 (20)	100 (20)	16 (22)
Obese	227 (25)	96 (19)	16 (22)

Figure 2: Male Patients by Weight and Race, Year 2000

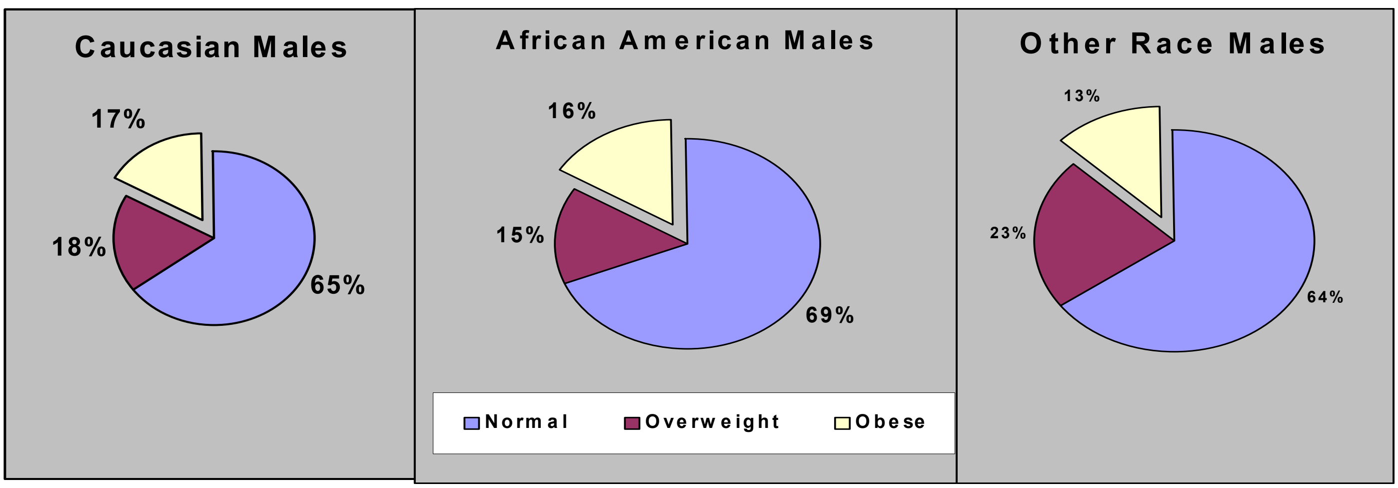
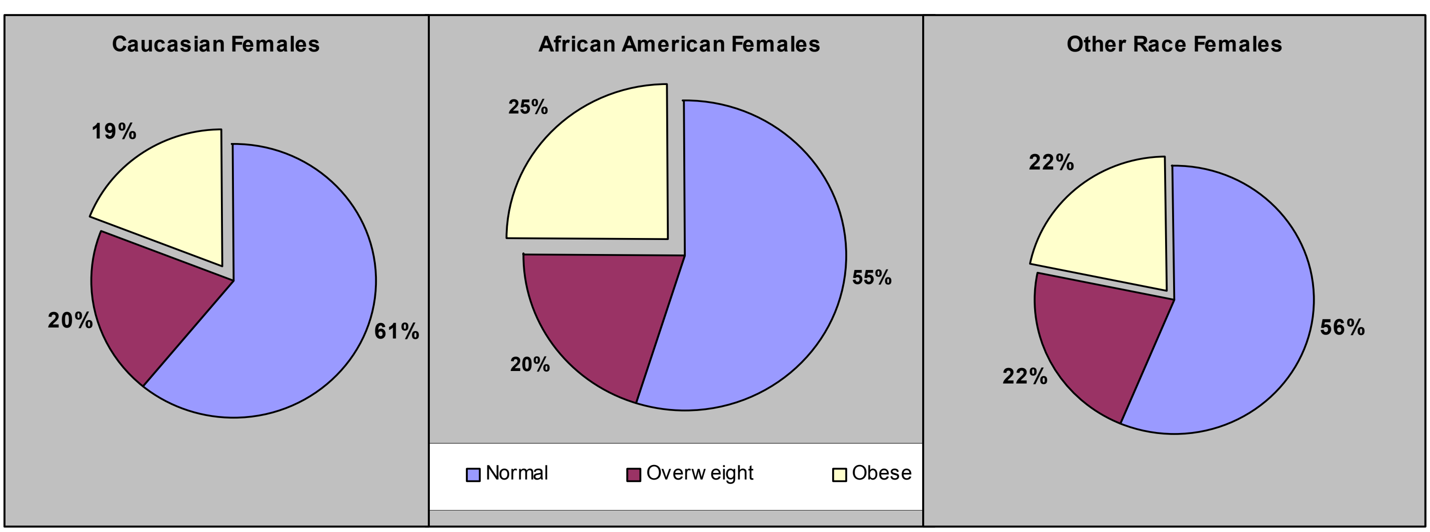


Figure 3: Female Patients by Weight and Race, Year 2000



Socioeconomic Status

Table 2 summarizes the age and income distributions by 3 body mass index categories for the patients selected in the Year 2000 electronic medical record query. The obese group is slightly older than the normal weight group. Income shows a negative association with BMI. Subjects with higher BMI have lower income.

Table 2. Mean and Standard Deviation of Age and Median Income (in $1000) by BMI for Year 2000 Study Cohort

Variable	Normal (n = 1521)	Overweight (n = 470)	Obese (n = 505)
Age	14.5 ± 2.0	14.8 ± 2.0	15.2 ± 1.9
Median Income (1000)	24.1 ± 8.9	23.2 ± 7.9	23.1 ± 7.9

Access to Play Space

There were no statistically significant differences between normal, overweight, and obese children in terms of their straight-line proximity to the nearest public play space (Table 3).

Table 3. Proximity to Play Space by BMI

	Mean distance (meters)	Std Dev (m)	n
Obese	567	450	505
Not obese	571	478	1991

Social Barriers

Table 4 summarizes mean indicator values representing crime rates, single parenting, and educational attainment for the 3 body mass index categories of the Year 2000 patients. The average crime rate is substantially higher for the obese group when compared with the normal weight group. The average proportion of single-parent households and proportion of persons 25+ without high school diploma slightly vary across the three categories of BMI.

Table 4. Mean and Standard Deviation of Age, Median Income (in $1000), Crime, Proportion of Persons 25+ with HS Diploma and Proportion of Single Parent by BMI for Year 2000 Study Cohort

Variable	Normal (n = 1521)	Overweight (n = 470)	Obese (n = 505)
Crimes per square mile	677.7 ± 707.9	667.9 ± 682.4	766.8 ± 761.2
Prop of single parent	17.2 ± 8.1	17.7 ± 7.9	18.0 ± 8.2
Prop of persons 25+ without HS diploma	34.3 ± 15.9	35.4 ± 15.4	35.0 ± 15.4

Multivariate Model

Bivariate analyses identified gender, age, race, single-parent households, median income and crime rate to be significant factors (0.05 significance level) in predicting the incidence of obesity in children. However, a multivariate logistic regression eliminated the effect of proportion of single-parent households and crime. The logistic regression indicated a significant interaction effect between race and gender on obesity. In the logistic regression model, a nonlinear relationship is observed between age and the incidence of childhood obesity.

Table 5 shows the results from multivariate logistic regression and Table 6 describes the estimates of the odds ratios for income and different groups of gender and race, where the reference group is white male.

Table 5: Parameter Estimates, Standard Error of the Estimates and P-values from Multivariate Polytomous Logistic Regression for Year 2000 Study Cohort

Parameter	Estimate	Standard Error	P-value
Intercept (Obese)	- 1.2773	0.1676	< 0.0001
Intercept (Overweight)	- 0.3242	0.1653	0.0499
(Age – 14.7)	0.1408	0.0217	< 0.0001
$(\text{Age} - 14.7)^2$	0.0152	0.0062	0.0144
Median Income	- 0.0117	0.0049	0.0166
Gender	0.0474	0.1395	---
Black	- 0.1880	0.1391	---
Others	- 0.0979	0.2697	---
Black x Gender	0.4421	0.1770	---
Others x Gender	0.3287	0.3649	---

P-value for the interaction effect between gender and race is 0.04

The odds of obesity (Table 6) relative to normal or overweight are estimated to be 1.4 times higher for black females than for white males, 1.3 times higher for other (race) females than for white males, but 0.8 times lower for black males than for white males and 0.9 times lower for other (race) males than for white males. For each increase of $10,000 in median income, the odds of obesity decrease by 11%. Since age has a nonlinear effect on obesity, the change in odds of obesity is not constant for each one-year increase in age. For example, a 13-year old child has 1.1 times higher odds of being obese than a 10-year old child; but a 16-year old child has 1.5 times higher odds of being obese than a 13-year old child.

Table 6: Point Estimates and 95% Confidence Intervals for Odds Ratios for Year 2000 Study Cohort

Factor	Estimate	95% Confidence Interval
Median Income	0.988	(0.979, 0.998)
Race and Gender		
White Male	1.000	Reference Group
White Female	1.049	(0.798, 1.378)
Black Male	0.829	(0.631, 1.088)
Black Female	1.352	(1.057, 1.729)
Others Male	0.907	(0.534, 1.538)
Others Female	1.321	(0.805, 2.167)

Phase II: Census Block Group-Level Analysis

Individual (Patient)-Level Demographics

In the study population consisting of the most recent measurements for all patients who were measured between the years 1996 and 2000 (Table 7), the estimated prevalence of childhood obesity is 21.5% and overweight is 16%. African Americans and Hispanics have slightly higher prevalence of obesity than white or other racial groups, with Hispanics having the highest rates of obesity. The prevalence of obesity is substantially higher in girls than in boys (Figures 4 and 5). The risk of obesity differs greatly across the six groups formed by race and gender. Hispanic girls have the highest risk of obesity while the boys in the “Other” category of race have the lowest risk of obesity.

Table 7. Distribution of BMI by Race and Gender for Years 1996-2000 Study Cohort

	Black (%)	*White (%)*	*Hispanic (%)*	*Other (%)*
Male				
Normal	3246 (65)	1820 (63)	198 (54)	132 (67)
Overweight	734 (15)	450 (16)	76 (21)	36 (18)
Obese	1021 (20)	620 (21)	94 (16)	28 (14)
Female				
Normal	3396 (60)	2041 (63)	185 (57)	115 (64)
Overweight	996 (18)	519 (16)	55 (17)	27 (15)
Obese	1302 (22)	660 (21)	82 (26)	38 (21)

Figure 4: Male Patients by Weight and Race, Years 1996 - 2000

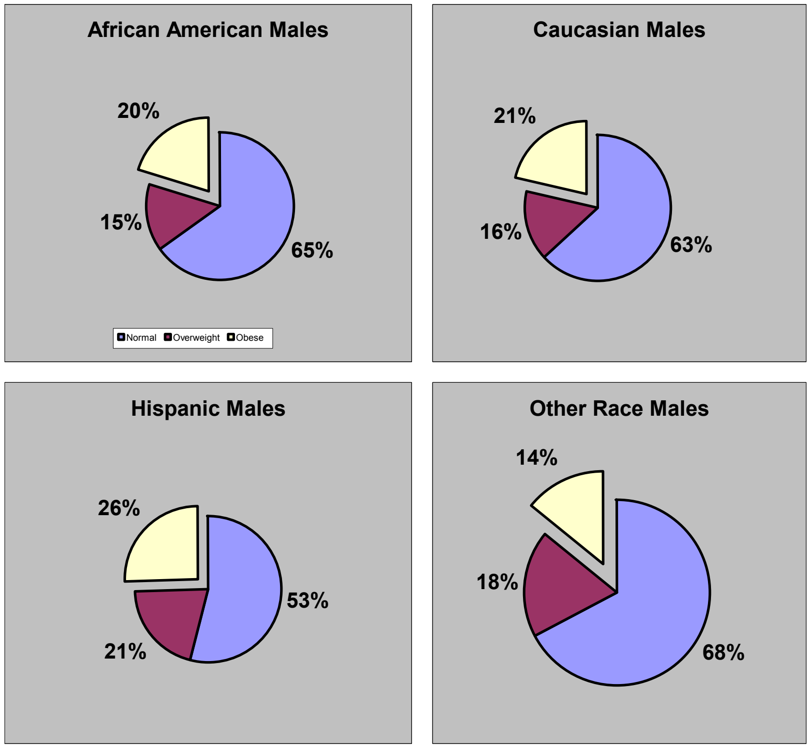
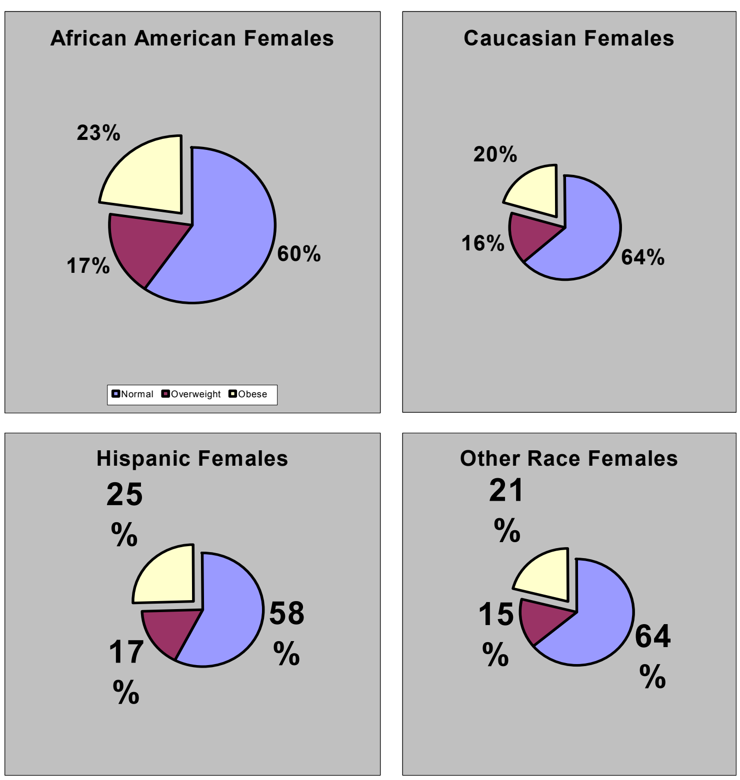


Figure 5: Female Patients by Weight and Race, Years 1996 - 2000



Socioeconomic Status

Table 8 summarizes the age and income distributions by 3 body mass index categories for the patients selected in the Year 1996-2000 electronic medical record query. The obese group is slightly older than the normal weight group (Figure 6). Income shows a negative association with BMI. Subjects with higher BMI have lower income (Figure 7).

Table 8. Summary Statistics on Age and Income Census Block Group Indicators by BMI for Years 1996-2000 patients

	Normal (n=11133)	Overweight (n=2893)	Obese (n=3845)
Age (years)	9.7 ± 4.24	10.6 ± 4.27	10.9 ± 4.06
Median Income (dollars)	$33,112 ± 13270	$32,647 ± 12,319	$31,925 ± 11,627

Figure 6: Patients by Weight and Age, Years 1996-2000

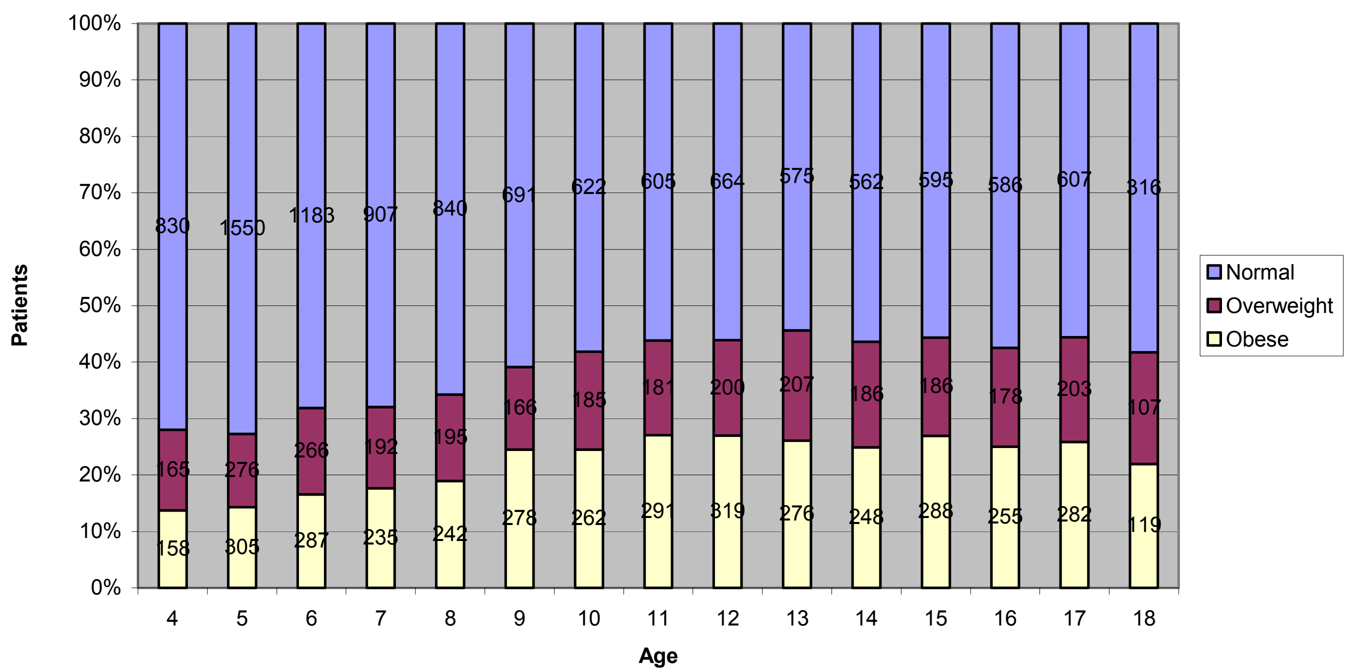
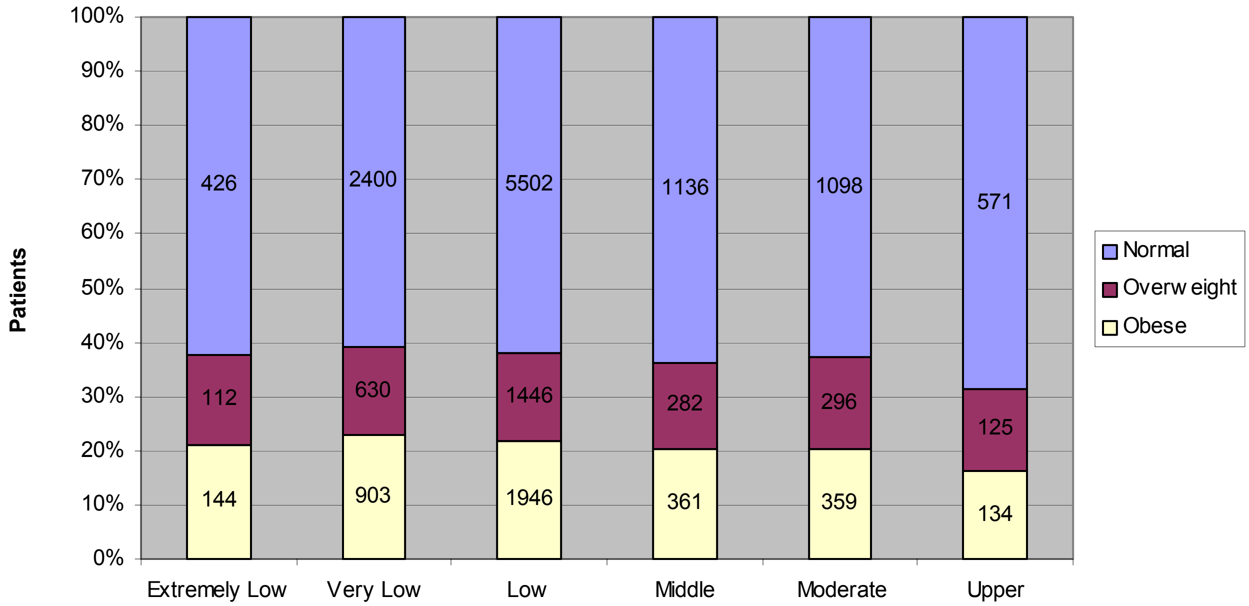


Figure 7: Patients by Weight and Median Family Income, Years 1996 - 2000



Access to Play Space

Since the results of the play space analysis were negative in the Phase I analysis, this measure was not repeated for the expanded cohort.

Social Barriers

Table 9 summarizes mean indicator values representing linguistic isolation, educational attainment, and single parenting for the 3 body mass index categories of the Year 2000 patients. From the perspective of census block groups, mean values for these three variables only slightly vary across the three categories of BMI.

Table 9. Summary Statistics on Linguistic Isolation, Educational Attainment, and Single Parenting Census Block Group Indicators by BMI for Years 1996-2000 patients

	Normal (n=11133)	Overweight (n=2893)	Obese (n=3845)
% Linguistic isolation	2.2 ± 3.64	2.2 ± 3.34	2.2 ± 3.54
% Adults without HS diploma	28.9 ± 14.5	29.1 ± 14.5	29.0 ± 13.9
% Single parent family	28.6 ± 14.5	29.0 ± 14.5	29.0 ± 13.9

There were minimal differences in average crime rates per square mile at the block group-level for the 3 categories of BMI (Table 10).

Table 10. Summary Statistics on Crime rate by BMI for Years 1996-2000 patients

	Normal (n=7681)	Overweight (n=1990)	Obese (n=2734)
Part One crimes per square mile	603 ± 431	605 ± 427	603 ± 427

Multivariate Model

Bivariate analyses identified gender, age, proportion of adults age 25 and older without high school diploma, and median income to be significant factors in predicting the incidence of obesity in children. However, a multivariate logistic regression eliminated the effect of proportion of adults age 25 and older without high school diploma. The logistic regression indicated a significant interaction effect between race and gender on obesity. In the logistic regression model, a nonlinear (quadratic) relationship is observed between age and the incidence of childhood obesity.
Table 11 shows the results from the multivariate logistic regression and Table 12 describes the estimates of the odds ratio for income, educational attainment and different groups of gender and race, where the reference group is white male.

Table 11: Parameter Estimates, Standard Error of the Estimates and P-values from Multivariate Logistic Regression for Year 1996 – 2000 Study Cohort

Parameter	Estimate	Standard Error	P-value
Intercept (Obese)	- 1.4933	0.1034	< 0.0001
Female	- 0.0713	0.0636	0.2627
African American	- 0.0464	0.0583	0.4261
Hispanic	0.3622	0.1297	0.0052
Other races	- 0.4255	0.2105	0.0433
Female & African American	0.1752	0.0793	0.0271
Female & Hispanic	0.0269	0.1879	0.8863
Female & Other race	0.5892	0.2833	0.0375
Age	0.0746	0.0049	< 0.0001
Age & gender	- 0.0109	0.0012	< 0.0001
Extremely low income	0.3654	0.1359	0.0072
Very low income	0.4380	0.1035	< 0.0001
Low income	0.3857	0.0988	< 0.0001
Moderate income	0.2960	0.1127	0.0086
Middle & upper income	0.2890	0.1123	0.0100

P-value for the interaction effect between gender and race is 0.04

The odds of obesity (Table 12) relative to normal or overweight are estimated to be highest for the Hispanic racial group (1.4 times higher for Hispanic males than for white males, 1.3 times higher for Hispanic females than for white males). The odds of obesity relative to normal or overweight are estimated to be lowest for the males in the "Other" racial group (0.654 times lower for "Other" race males than for white males). As noted previously, an inverse relationship was noted to exist between census block Median Family Income and prevalence of obesity. However, it should be noted that those children residing in block groups that had "extremely low" income had a lower risk of obesity in comparison with those children residing in the block groups with "very low" and "low" median family income. Age was again noted to have a nonlinear effect on obesity; the change in odds of obesity is not constant for each one-year increase in age.

Table 12: Point Estimates and 95% Confidence Intervals for Odds Ratios for Year 1996 - 2000 Study Cohort

Factor	Estimate	95% Confidence Interval
Extremely low income	1.441	(1.104, 1.881)
Very low income	1.550	(1.265, 1.898)
Low income	1.471	(1.212, 1.785)
Moderate income	1.345	(1.078, 1.677)
Middle income	1.335	(1.071, 1.664)
Upper income	1.000	Reference Group
Race and Gender		
White Male	1.000	Reference Group
White Female	0.931	(0.822, 1.055)
Hispanic Male	1.437	(1.114, 1.852)
Hispanic Female	1.374	(1.050, 1.799)
Black Male	0.955	(0.852, 1.070)
Black Female	1.059	(0.948, 1.184)
Others Male	0.654	(0.433, 0.987)
Others Female	1.097	(0.756, 1.592)

Spatial Analysis

We mapped the location of obese patients with several socioeconomic variables to determine if there are relationships between obesity and environmental factors that were not identified in the statistical analysis. In general, there are no discernable spatial relationships between obesity and the environmental factors. The most notable patterns seen between obesity and two of the indicators, income and educational attainment, reflect the findings of the statistical analysis.

The distribution of 1999 median family income by census block group is shown in Map 5 in Appendix B. The lower income areas are located near downtown Indianapolis, which is also where the largest number of the patients included in this study live (see Map 1 in Appendix B).

To examine the spatial relationship between obesity and income, we divided up the block groups based on their prevalence of obesity. For each block group, we calculated the percent of all patients age 4-18 residing in the block group that is obese. We determined the median of those percentages to be 20%. Next we compared the median family income classifications of those block groups containing greater than 20% obese patients to those block groups with less than 20% obese. A comparison of the maps shows a negative correlation between obesity and block group income (see Maps 5 and 6 in Appendix B). There are more block groups above the median percent obese that are categorized as low and very low income than for those block groups with less than the median percent obese.

We used the same methodology to determine the spatial relationship between the prevalence of obesity and educational attainment. Our comparison of the maps showed that there are more block groups that fall outside of the norm for "percent population 25 and over with no high school diploma" for those block groups with the greatest prevalence of obesity (see Maps 9 and 10 in Appendix B). This shows that there is a spatial relationship between the two factors but does not suggest a positive or negative association.

There is no obvious pattern in the distribution of obese patients in Marion County, which may contribute to the lack of a discernable spatial relationship between the prevalence of obesity and neighborhood socioeconomic indicators (see Map 3 in Appendix B). There are other methodologies that should be explored in future research that will contribute to the body of knowledge as researchers try to understand of the relationships between these variables. The use of GIS technology in medical research is still new, and applying methodologies used in other areas will further this field of research.

After we completed the statistical analysis, we selected those block groups with the greatest risk of obesity based on income and educational attainment (see Map 11 in Appendix B). We selected block groups categorized as low and very low income and those block groups with greater than 56.9% with no high school diploma. These high-risk areas are neighborhoods in which solution-based programs might be targeted and are areas that should be used for more focused study in the future.

DISCUSSION

Results of this study show significant associations between environmental factors that relate to socioeconomic status at the census tract and block group-levels and risk of obesity in children ages 4-18 years. Upon examining census tract and census block group levels of educational attainment and income, we found both of these factors had a significant inverse association with the risk of obesity in children in bivariate analyses. However, when the factors were simultaneously entered into a logistic regression, income emerged as the stronger predictor of obesity. We observed that as the median family income of a census block group decreases, the risk of obesity in children residing within the block group rises. This is true until the median family income of the block group has fallen into the "extremely low" category, in which case the risk of obesity begins to decline, though the obesity risk is still greater than the reference category of "upper" income block groups.

The association between low socioeconomic status (SES) and increased obesity risk has only recently been observed with consistency in the pediatric age groups. A 1975 report by Garn and colleagues found that obesity was associated with higher socioeconomic status in early childhood, and lower SES in adolescent females.[66] A review of the literature through the late 1980's by Sobal and Stunkard regarding socioeconomic status and childhood obesity found that published studies were widely disparate in the reporting of the direction of a relationship between SES and obesity, or even the existence of any relationship.[67] In 1992, Sorenson and colleagues reported a 2.2-fold increased incidence of childhood obesity in children living in dilapidated living conditions.[68] Strauss and Knight recently reported the results of a prospective study in which children from low income families had an almost threefold increased risk of developing obesity.[69] Typically, those with socioeconomic disadvantage have worse health status; however in the case of childhood obesity, the role that socioeconomic factors play in determining levels of health and influencing behavioral and psychosocial risk factors remains unclear. This study expands our knowledge of the association between SES and obesity risk as it, to our knowledge, is the first large population-based study to examine *environmental* (rather than individual) SES as a predictor of obesity in children.

Environmental SES is a key consideration in the investigation of chronic diseases with strong behavioral components such as obesity. Characteristics of local geographic areas (e.g. neighborhoods as represented by Census administrative regions) almost certainly have significant effects on the behavior of residents within the region. Neighborhoods are where one makes connections to people and becomes part of a social network. The social network provides access to information (e.g. availability of health services), influences choices (e.g. leisure activities, planning for the future), and creates cooperative opportunities. Therefore, neighborhoods can be conceptualized as generating social capital and cultural capital that represent concrete targets for interventions aimed at improving self-management. When a neighborhood has low SES, health can be adversely impacted through a number of pathways. In addition to the economic impacts of low SES, such as inadequate access to such things as health care, low SES likely mediates health behavior through psychosocial pathways of stress, decreased self-esteem, and social isolation. If we can design effective strategies to combat the deleterious effects of low environmental SES, then we stand to empower vulnerable populations to make healthy choices. The potential gain on such a wide scale is clearly a valuable avenue of inquiry and should be further explored alongside individual biomedical factors.

We specifically analyzed several environmental factors that previous studies identified as potentially important determinants of physical activity. A recent U.S. population-based study by King, et al., examined features of the built environment (e.g. sidewalks) and social environment (e.g. levels of crime) as determinants of physical activity.[70] The researchers identified the presence of enjoyable scenery as a positive determinant of physical activity, and perceived lack of a safe place to exercise as a significant barrier. These findings have been corroborated in a cross-sectional study by Brownson, et al., in which the presence of sidewalks and enjoyable scenery were found to positively correlate with physical activity.[71] Studies by the Centers for

Disease Control and Prevention indicate that lack of structures or facilities, such as sidewalks and parks, as well as fears about safety are significant barriers to physical activity.[72] Studies such as these point to the built environment as an amenable and potentially effective area for environmental intervention to increase levels of physical activity. We examined each study subject's proximity to the closest park, greenway, YMCA, or after school program as a proxy measure for access to public play space. We also examined census administrative region rates of crime, single parenting, and linguistic isolation as factors that would pose social barriers to physical activity.

Our study found that there were no significant differences in straight-line proximities to the nearest public play space among normal weight, overweight, and obese children. The issue of defining geographically based access to opportunities for exercise is difficult. Almost certainly, straight-line distance is too crude a measure/proxy for access to play space. Factors such as availability of transportation and physical barriers such as walls, waterways, and busy roadways were not considered. We are defining strategies to operationalize each factor for incorporation into the model. One strategy for operationalizing play space involves determining the geographic density of public play space resources within regions such as census tracts.

Our findings regarding barriers to physical activity varied depending on the time and geographic frames of the analysis. In bivariate analyses of the 1-year study cohort and census tract data, higher rates of crime and single-parenting were significantly associated with an increased risk of obesity. However, when income was controlled for as a co-variate, neither rates of crime nor single parenting remained significant predictors of obesity. In bivariate analyses of the 5-year study cohort and census block group data, there were no significant associations between risk of obesity and living in census administrative region with high rates of crime, single parenting, or linguistic isolation.

Individual patient factors of race, gender, and age were all significantly associated with risk of obesity. The racial disparities seen in studies of adult patients with obesity are also seen in this pediatric cohort.[5, 7, 8, 73] Obesity was more prevalent in the study minority populations, with Hispanics constituting the group most at risk. The Latino population of Marion County is rapidly growing, and certain neighborhoods have radically changed to reflect this dynamic demographic change. Issues relating to immigration, acculturation, and race will likely have significant impact on public health considerations regarding obesity risk. Obesity was also noted more often in the female study subjects and in the older age brackets; again, this reflects previously reported data for both children and adults

Systems-based environmental prevention efforts, in addition to programs or therapeutics aimed at individuals, are urgently needed to address the environmental pressures for overeating and sedentary behavior that pervade the United States. We have described here a unique convergence of technologies and research efforts that will deepen our understanding of the environmental context of childhood obesity and enable more precise targeting of systems-based environmental prevention efforts. We intend to continue refining our multivariate model of environmental obesity risk factors; subsequent efforts will specifically focus on incorporating additional factors that influence dietary behaviors. A recent study by Morland, et al. examined the effect of local food environments and resident report of dietary intake.[74] The study showed that the presence of supermarkets within census tracts significantly increased fruit and vegetable intake, particularly among African American residents. The knowledge gained from this ongoing research effort will inform the design of future:

1. Screening studies linking environmental characteristics, such as descriptions of the built environment, with disease, such as obesity;

2. Interventional studies that modify environmental infrastructure to promote healthy behavior such as routine physical activity and healthy diet;

3. Interventional studies that modify the social environment to promote healthy behavior through modalities such as targeted educational programs; and

4. Educational materials to inform the public regarding community and population determinants of obesity.

COMMUNITY PROCESS

This research is very timely for Indianapolis. The Alliance for Health Promotion is forming a collaborative, the “Strategic Thinking Coalition,” to address the issue of obesity in Indianapolis. While the mission and goals of this new group are in the process of being defined, it is clear that the group will provide a means to affect the community in a more comprehensive way and will be a strong forum for developing collaborations around this topic. Key stakeholders and policy makers, including the Mayor’s Office, United Way, health organizations, neighborhood organizations, educators, fitness nutrition experts, members of the media, and local foundations, have gathered around a common table to develop strategies that address the issue of obesity through such initiatives as educational and awareness programs.

One of the first steps the group is taking is to review existing research and literature regarding obesity prevention and treatment. Another immediate next step is the conduct of an Indianapolis-based needs assessment to give better focus to their mission statement. The collaborative has decided to focus on both children and adults, recognizing the importance of affecting change through the family unit. Our study findings will be shared with the “Strategic Thinking Coalition,” and will contribute to the understanding of the status of childhood obesity in Indianapolis. It will also provide guidance on specific neighborhoods and populations that should be considered for educational programs and initiatives from this group.

As partners in the SAVI project, The Polis Center and United Way of Central Indiana have met to discuss the implications of this analysis for local health initiatives. United Way plans to use the results of this analysis to guide policy development on two of their six Impact councils: “Community Health and Well-Being” and “Children and Youth.” United Way established their six impact councils, each made up of community volunteers, human service professionals, funding partners, and consumers of services, to address critical issues facing Central Indiana. Specifically, the Community Health and Well-Being Council will likely use the results to assist in deciding where to deploy programs to address their impact target of promoting healthy lifestyles. They will also use this analysis to shape strategies and types of programs for implementation. This information will also be used to track future performance of strategies for promoting healthy lifestyles.

We will work with United Way of Central Indiana to share the findings of this analysis and the work of the impact councils with the Marion County Health and Hospital Corporation. The Marion County Health and Hospital Corporation is the agency responsible for setting public health policy in Indianapolis.

We will also work to disseminate the results to the medical community to further research in this and related fields. For example, David Marrero, PhD., director of the Diabetes Research and Training Center (DRTC), is interested in the results of this analysis and how it can be applied to diabetes intervention and prevention. This report will also be shared with Mary Beth Riner, DNS, faculty in the IU School of Nursing, who is interested in the relationship between obesity and asthma. She is also interested in applying the methodology used in this study to analyze social and environmental predictors of asthma. The findings will be presented to pediatric residents at various teaching conferences and to faculty in the IU Department of Pediatrics.

Indianapolis has developed an extensive greenway system throughout the city with the goal of promoting physical activity and non-motorized travel. The Indy Greenways Administrator, Ray Irvin, is involved in research monitoring the use of the trail system and has researched predictors of trail usage including demographics, weather, days of the week, and local events in the area. He is also interested in monitoring obesity around the trails. The results of this study will be shared with Indy Parks and Recreation, which may use the findings of this and subsequent research efforts to determine where to locate greenways and to establish baseline data for monitoring the impact of the greenways on obesity in the surrounding areas.

PROJECT COLLABORATORS

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APPENDIX A: DATA DOCUMENTATION

Phase I Indicators

Category	Indicator	Measured As	Data Year	Geography	Source
Individual-level Indicators	Age	Age of patient	2000	Collected as address. Geocoded.	Regenstrief Medical Records System (RMRS)
	Race	Race of patient	2000	Collected as address. Geocoded.	RMRS
	Gender	Gender of patient	2000	Collected as address. Geocoded.	RMRS
	Body Mass Index	BMI of patient	2000	Calculated using patient height and weight	RMRS
Socioeconomic Indicators	Educational Attainment	% of population 25 and older without a high school degree	1990	Census tract	Social Assets and Vulnerabilities Indicators (SAVI) database Source data: US Census Bureau Summary Tape File 3
	Income	Median family income as a percent of MSA median family income	1990	Census tract	SAVI database Source data: US Census Bureau Summary Tape File 3
Physical Activity Opportunity Indicators	Proximity to Play space	Distance to nearest YMCA	2001	Calculated using GIS	YMCA locations: SAVI database
	Proximity to Play space	Distance to nearest City Park	2002	Calculated using GIS	City Park locations: Department of Metropolitan Development, City of Indianapolis

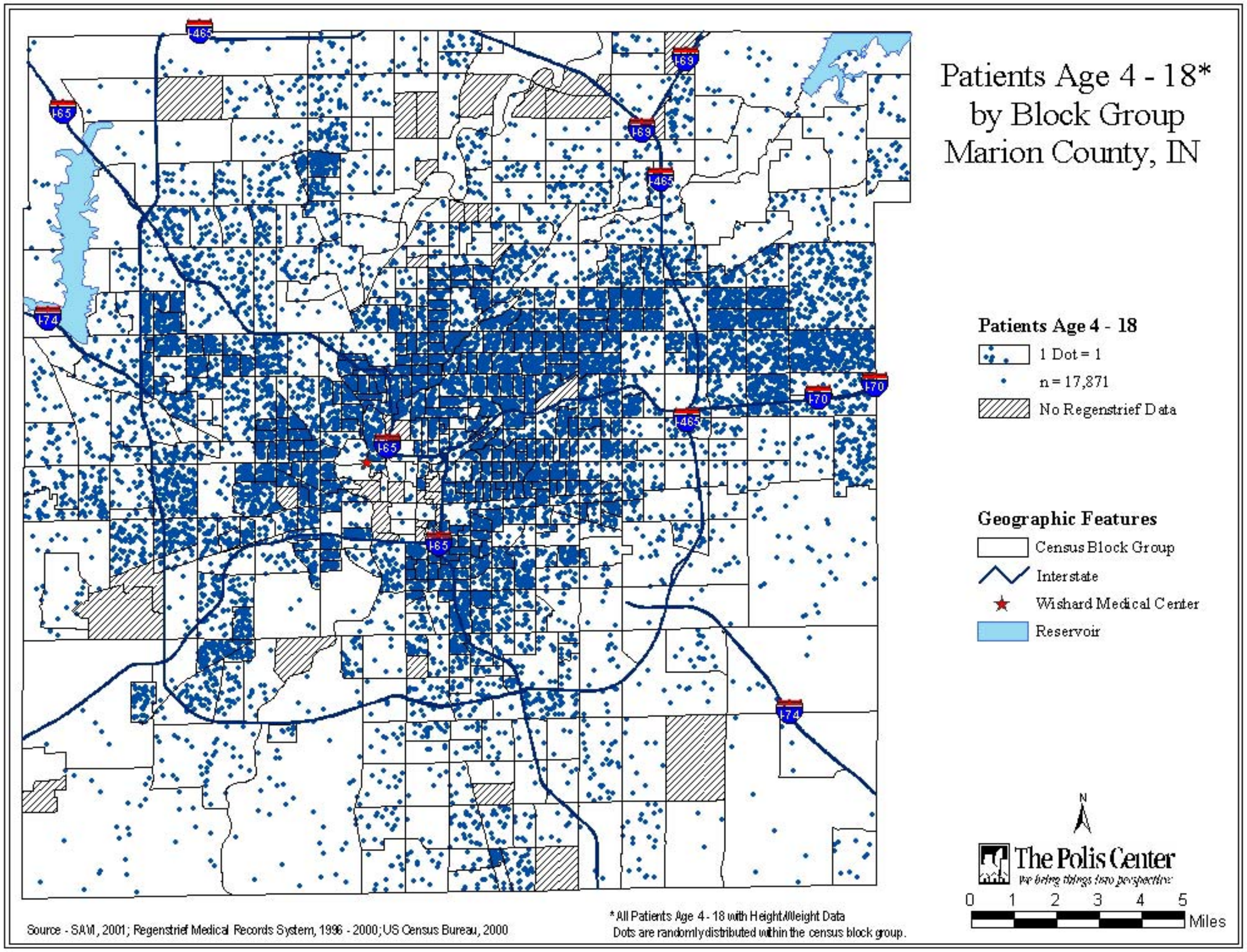
Category	Indicator	Measured As	Data Year	Geography	Source
Physical Activity Opportunity Indicators (cont)	Proximity to Play space	Distance to nearest greenway	2002	Calculated using GIS	Greenway locations: Department of Metropolitan Development, City of Indianapolis
	Proximity to Play space	Distance to nearest after-school program	2001	Calculated using GIS	After school program locations: SAVI database
	Distance to nearest play space	Calculated as distance from patient's home to nearest YMCA, city park greenway, or after school program	2002	Calculated using GIS	Calculated
Barriers to Exercise Indicators	Single-parent families	% of families that are single-parent	1990	Census tract	SAVI database Source data: US Census Bureau Summary Tape File 3
	Crime	Violent crime rate per square mile (includes: criminal homicide, robbery, aggravated assault, burglary, larceny, motor vehicle theft, rape and simple assaults)	1990	Census tract; Collected only for areas in the Indianapolis Police Department service area	SAVI database Source data: Indianapolis Police Department

Phase II Indicators

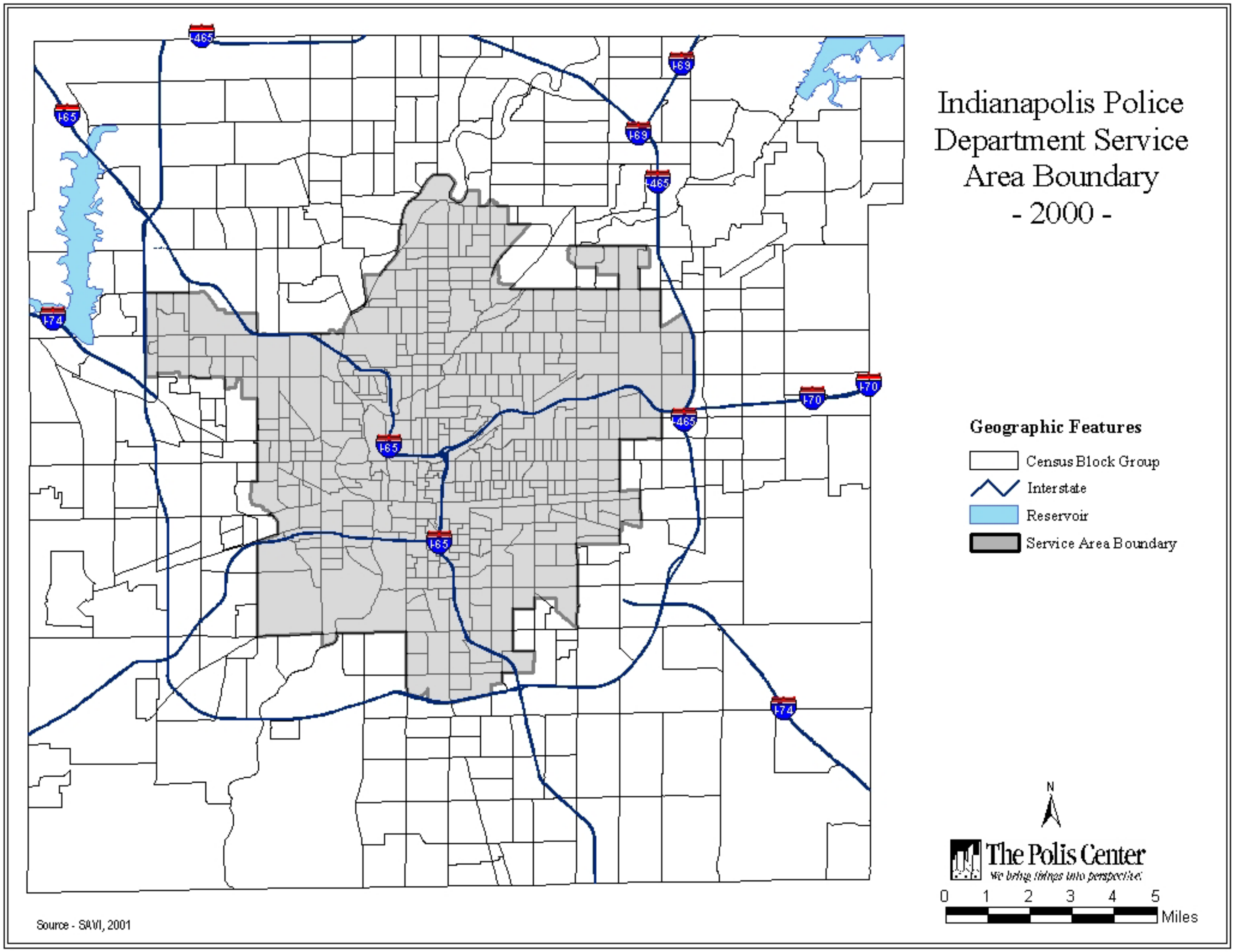
Category	Indicator	Measured As	Data Year	Geography	Source
Individual-level Indicators	Age	Age of patient at the time of latest visit between 1996-2000	1996-2000	Collected as address. Geocoded.	Regenstrief Medical Records System (RMRS)
	Race	Race of patient	1996-2000	Collected as address. Geocoded.	RMRS
	Gender	Gender of patient	1996-2000	Collected as address. Geocoded.	RMRS
	Body Mass Index Percentile	BMI percentile of patient at the time of latest visit between 1996-2000	1996-2000	Calculated using patient height and weight	RMRS
Socioeconomic Indicators	Educational Attainment	% of population 25 and older without a high school degree	2000	Census block group	US Census Bureau Summary File 3
	Income	Median family income as a percent of MSA median family income	2000	Census block group Calculated	US Census Bureau Summary File 3
Barriers to Exercise Indicators	Single-parent families	% of families that are single-parent	2000	Census block group	US Census Bureau Summary File 3
	Linguistic Isolation	Percent of Linguistically Isolated Households	2000	Census block group	US Census Bureau Summary File 3
	Crime	Violent crime rate per square mile (includes: criminal homicide, robbery, aggravated assault, burglary, larceny, motor vehicle theft, rape, and simple assaults)	2000	Census block group; Collected only for areas in the Indianapolis Police Department service area	Social Assets and Vulnerabilities Indicators database Source data: Indianapolis Police Department

APPENDIX B: MAPS

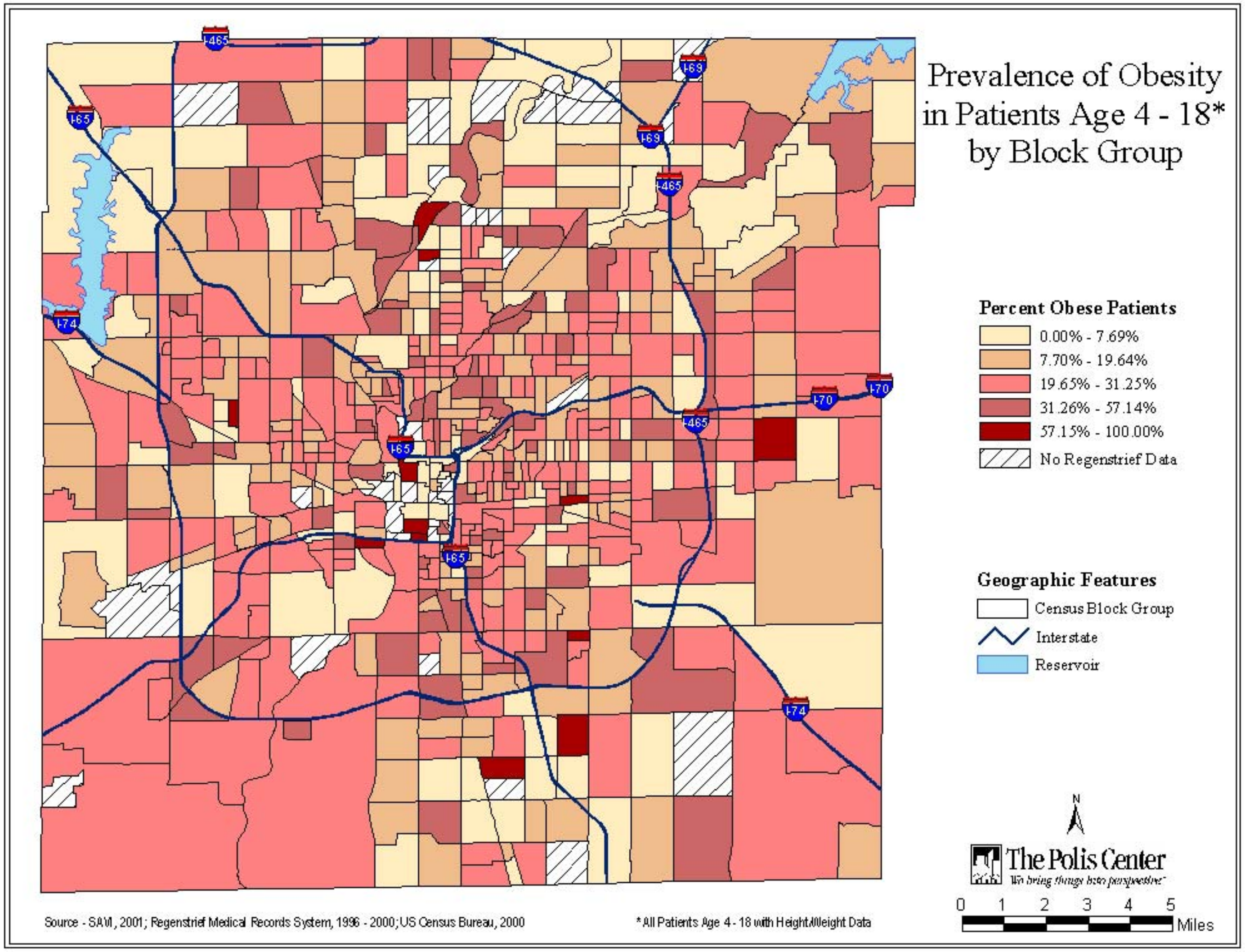
MAP 1: Distribution of Patients Age 4-18, 1996-2000



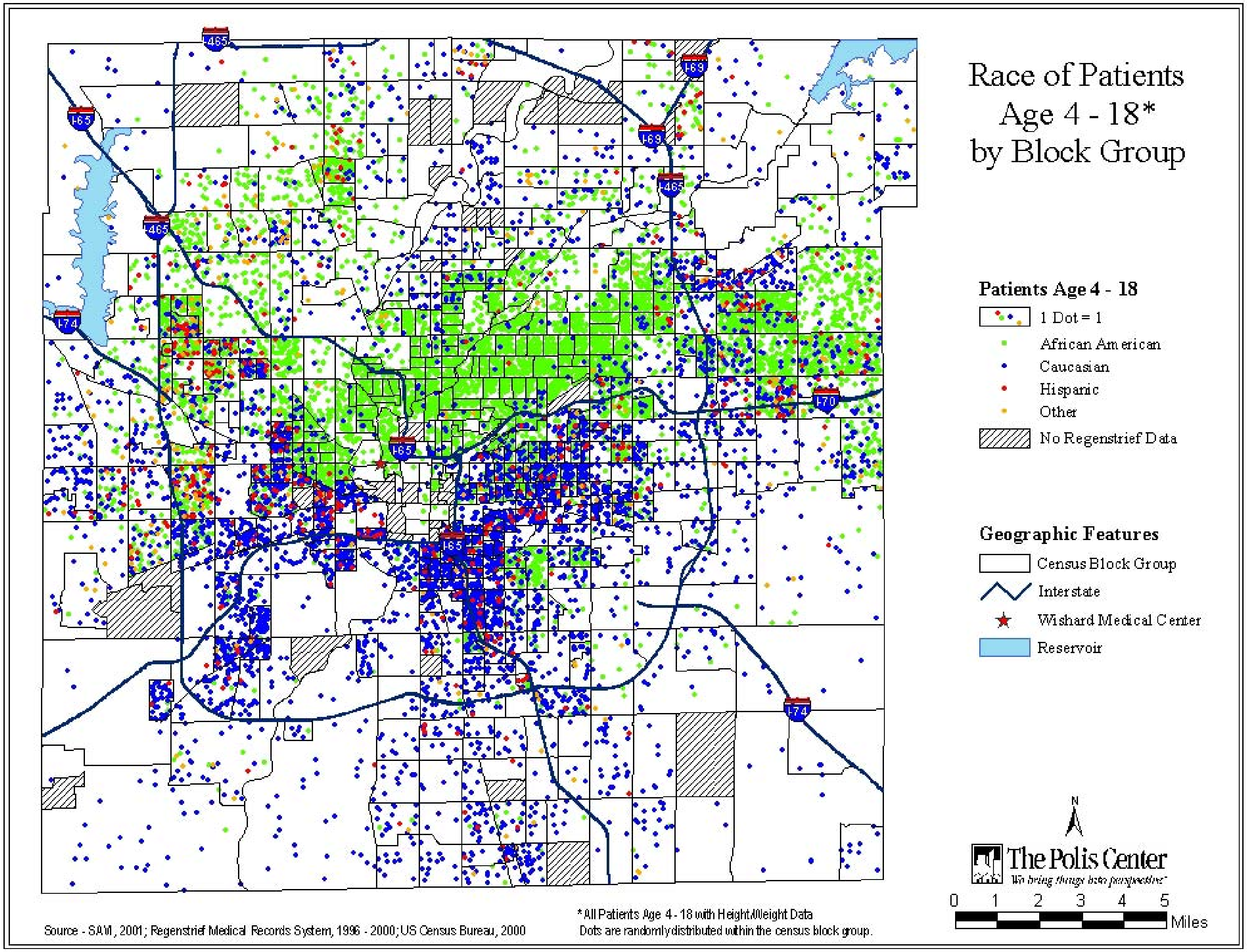
MAP 2: Indianapolis Police Department Service Area Boundary



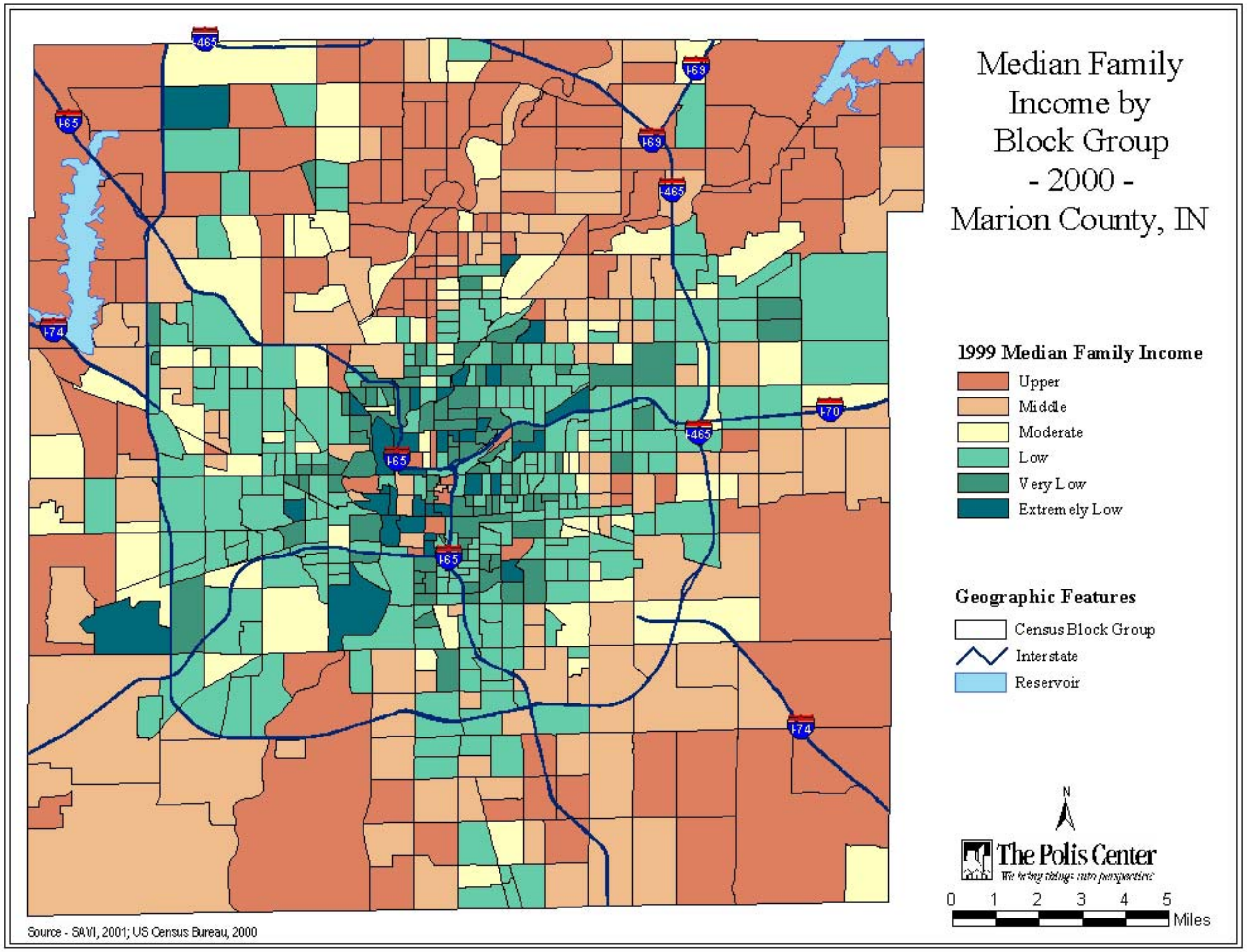
MAP 3: Prevalence of Obesity in Patients Age 4-18 by Block Group



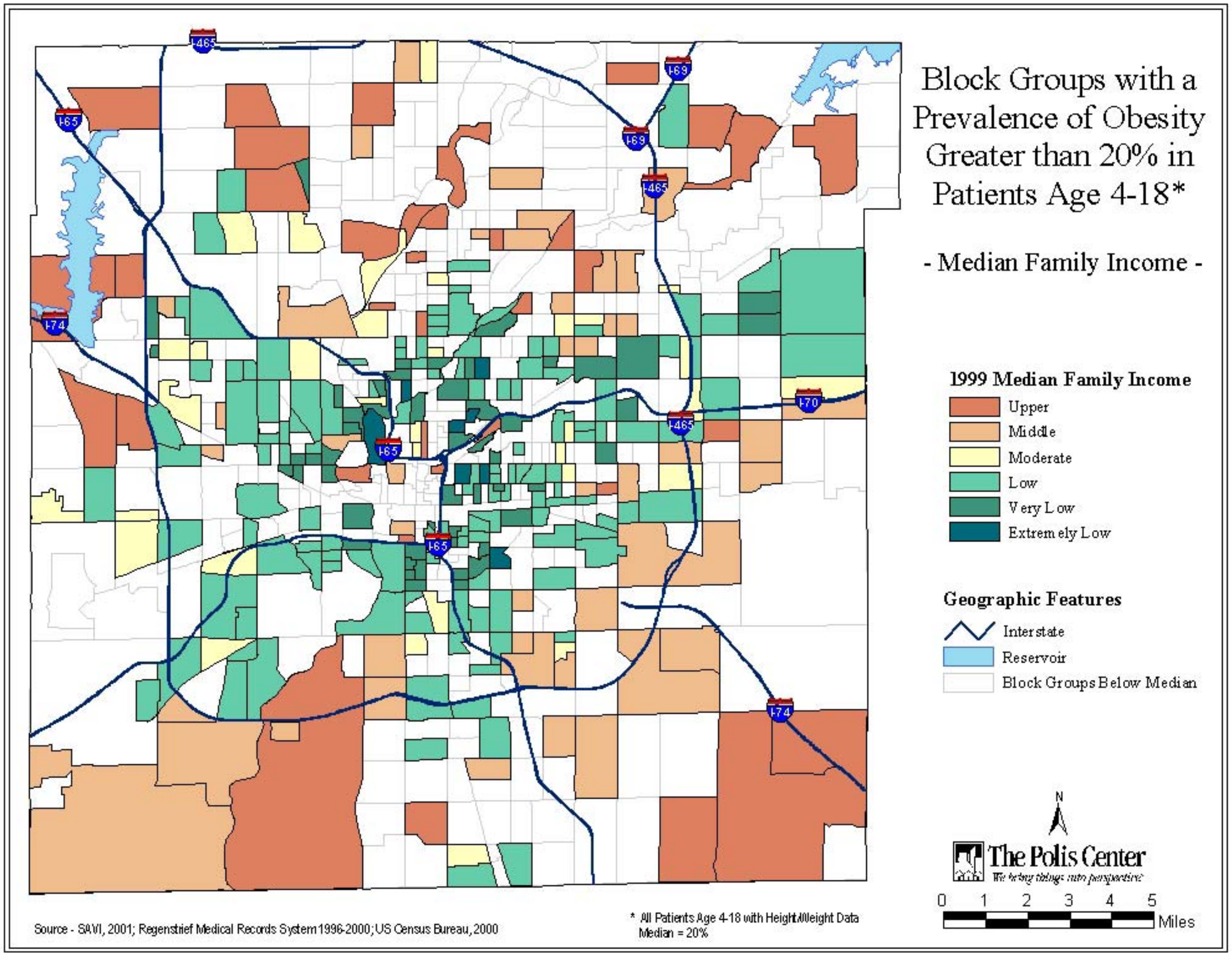
MAP 4: Distribution of Obese Patients Age 4-18 by Race, 1996-2000



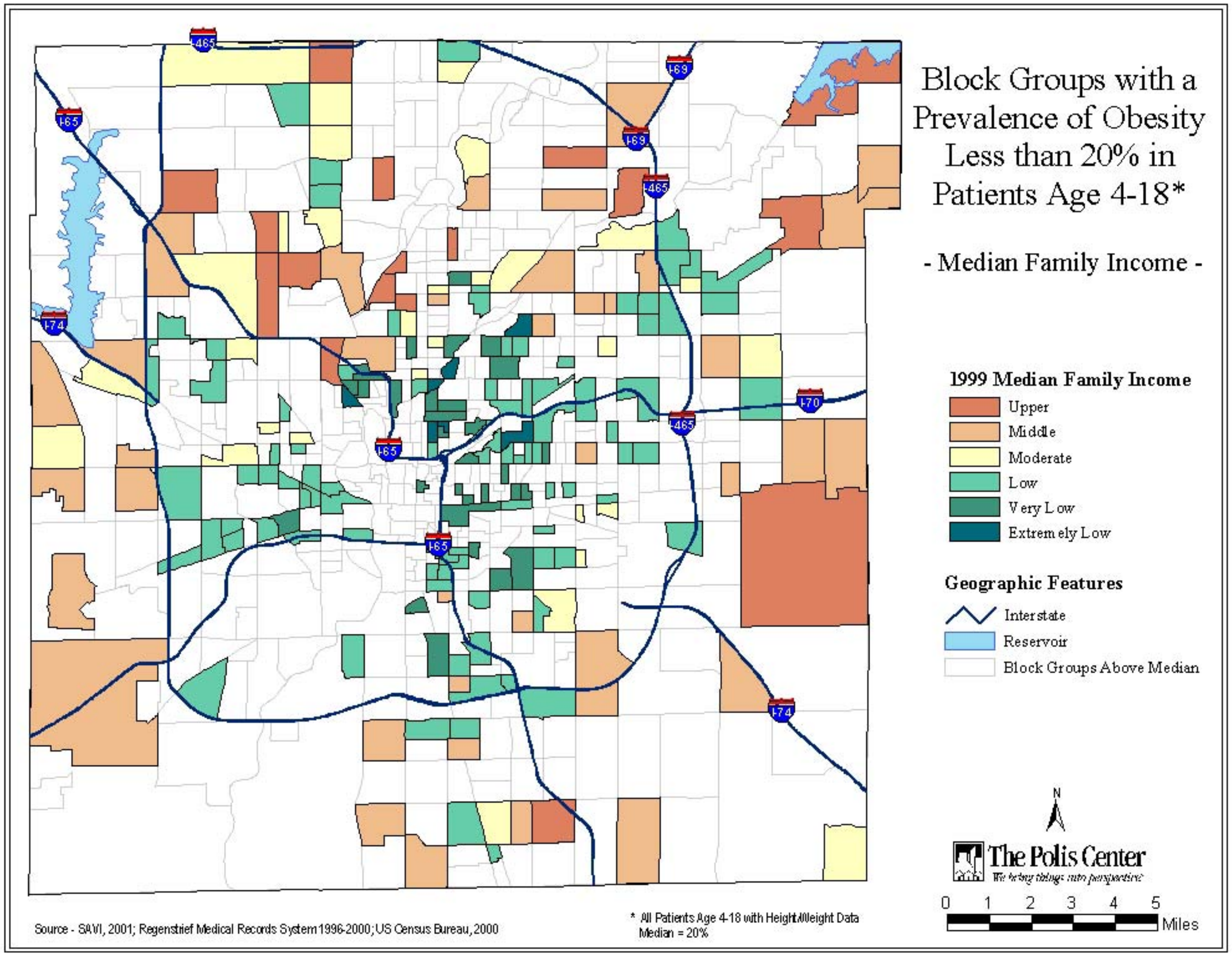
MAP 5: 1999 Median Family Income by Block Group



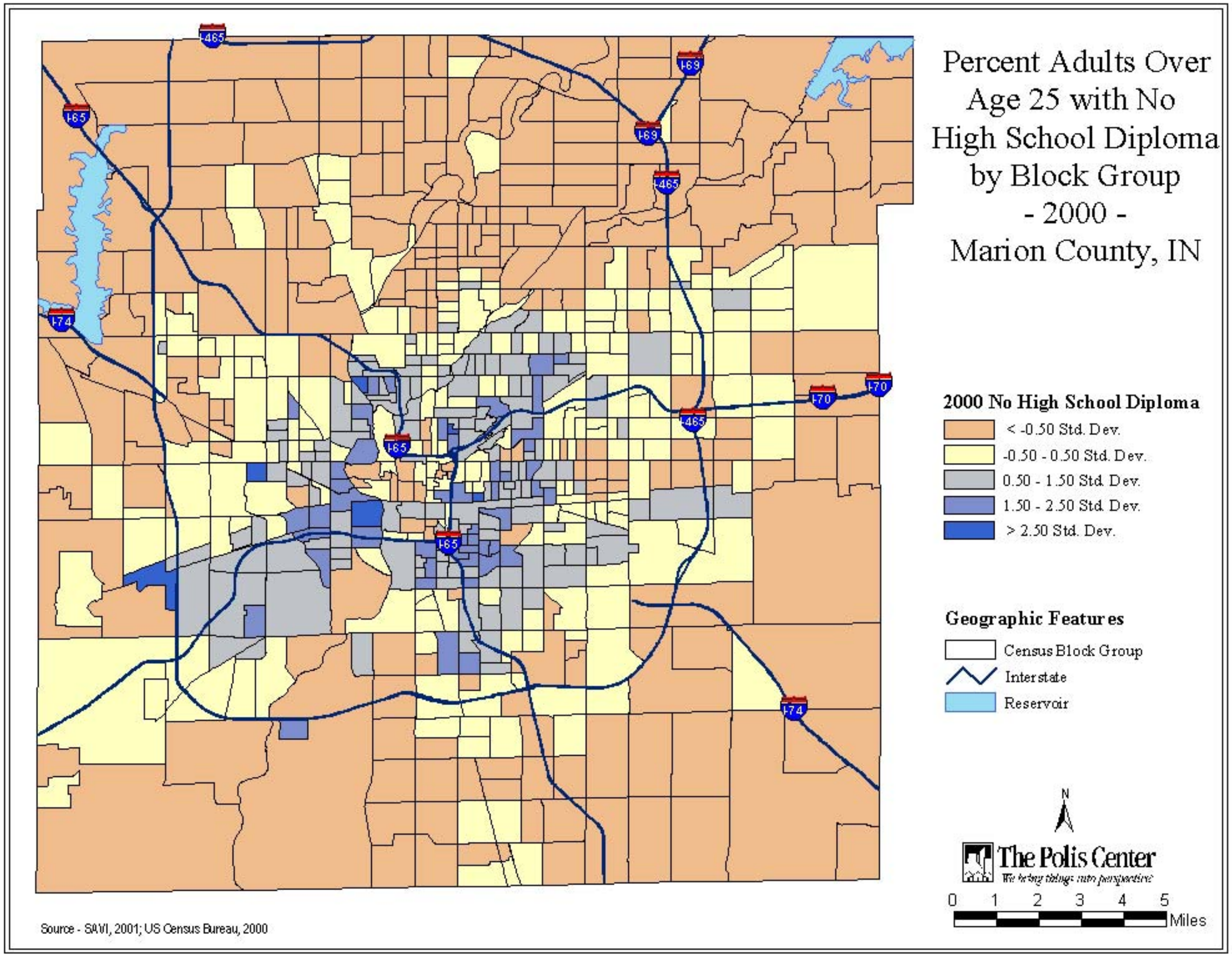
MAP 6: Highest Prevalence of Obesity and Median Family Income



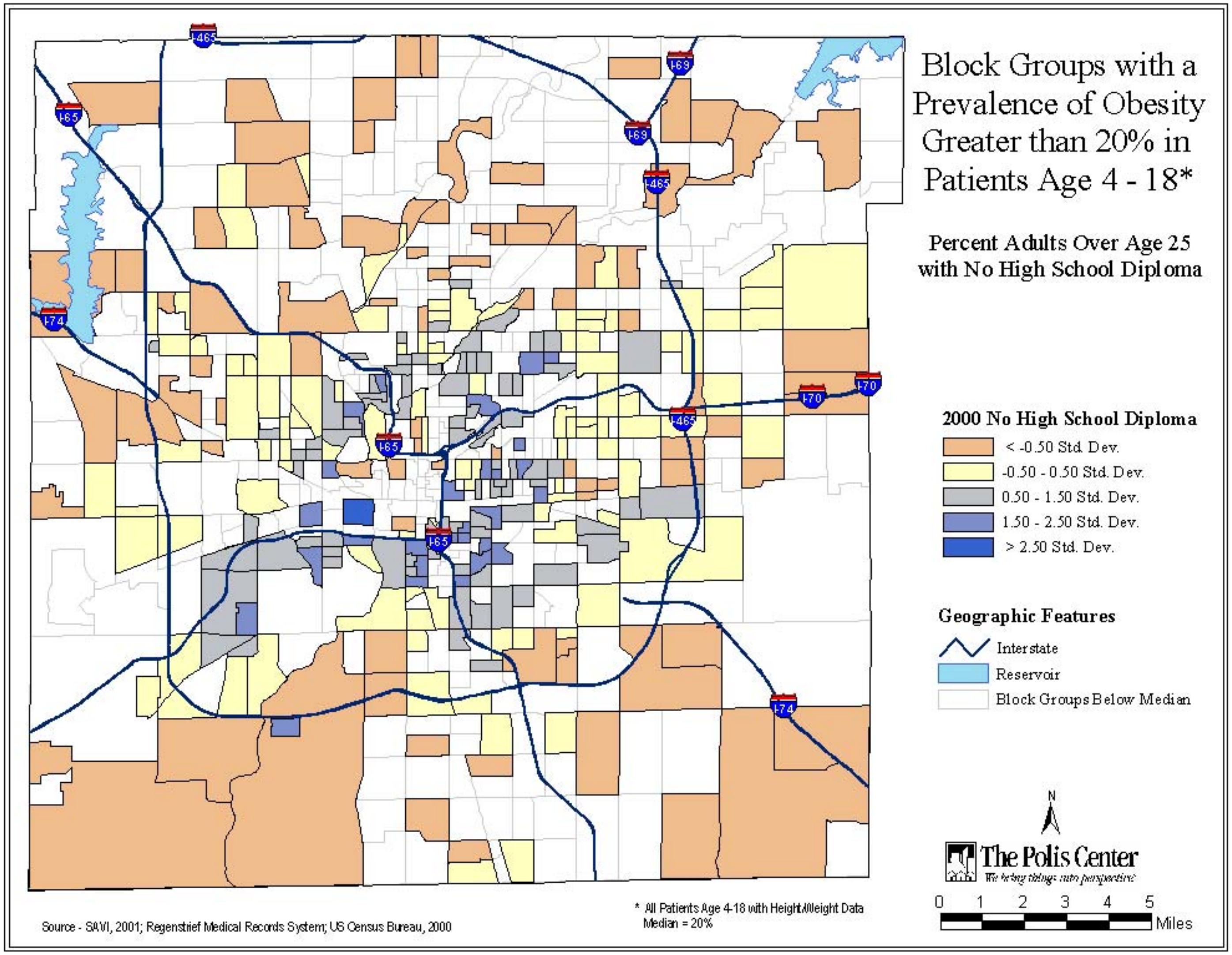
MAP 7: Lowest Prevalence of Obesity and Median Family Income



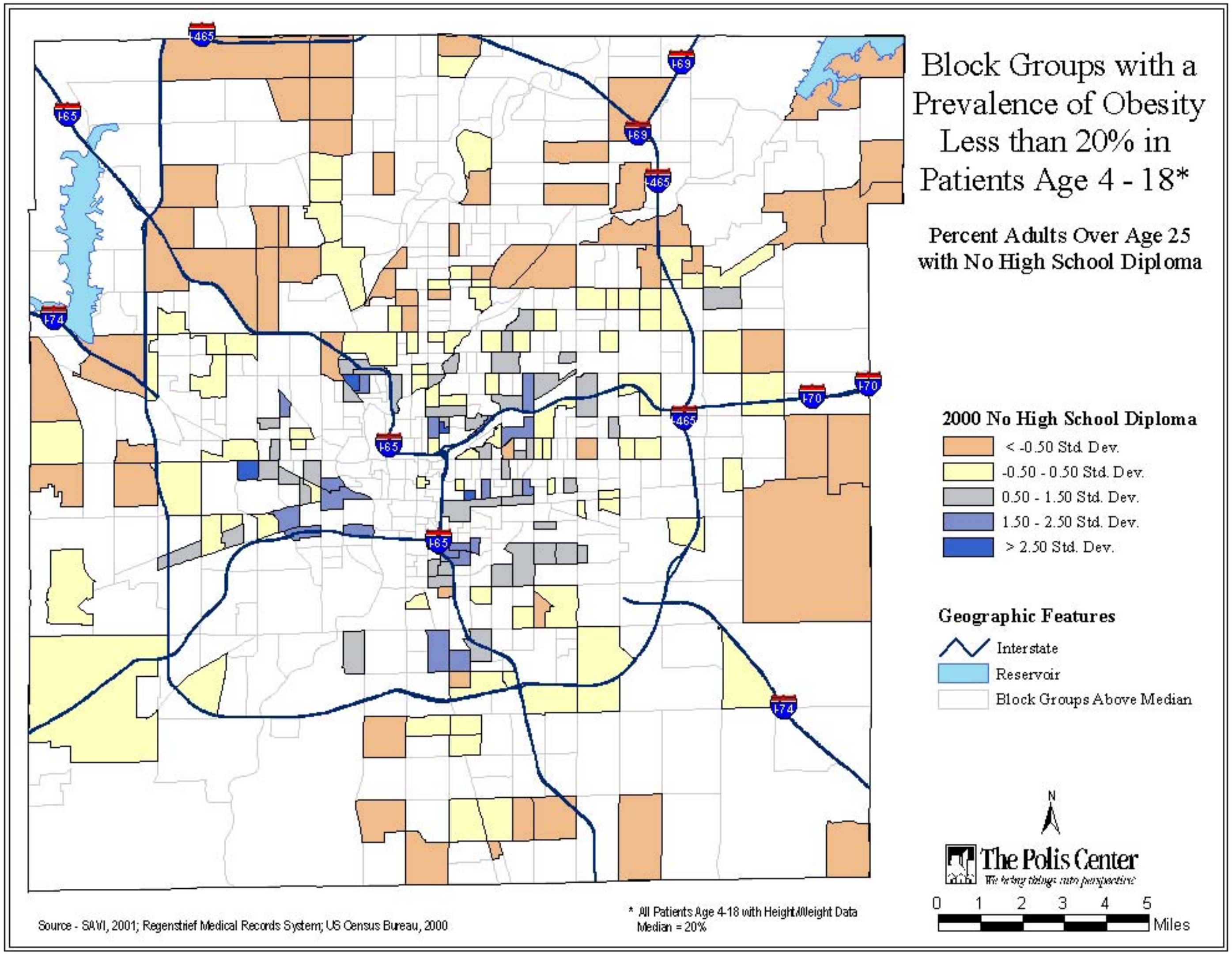
MAP 8: Educational Attainment



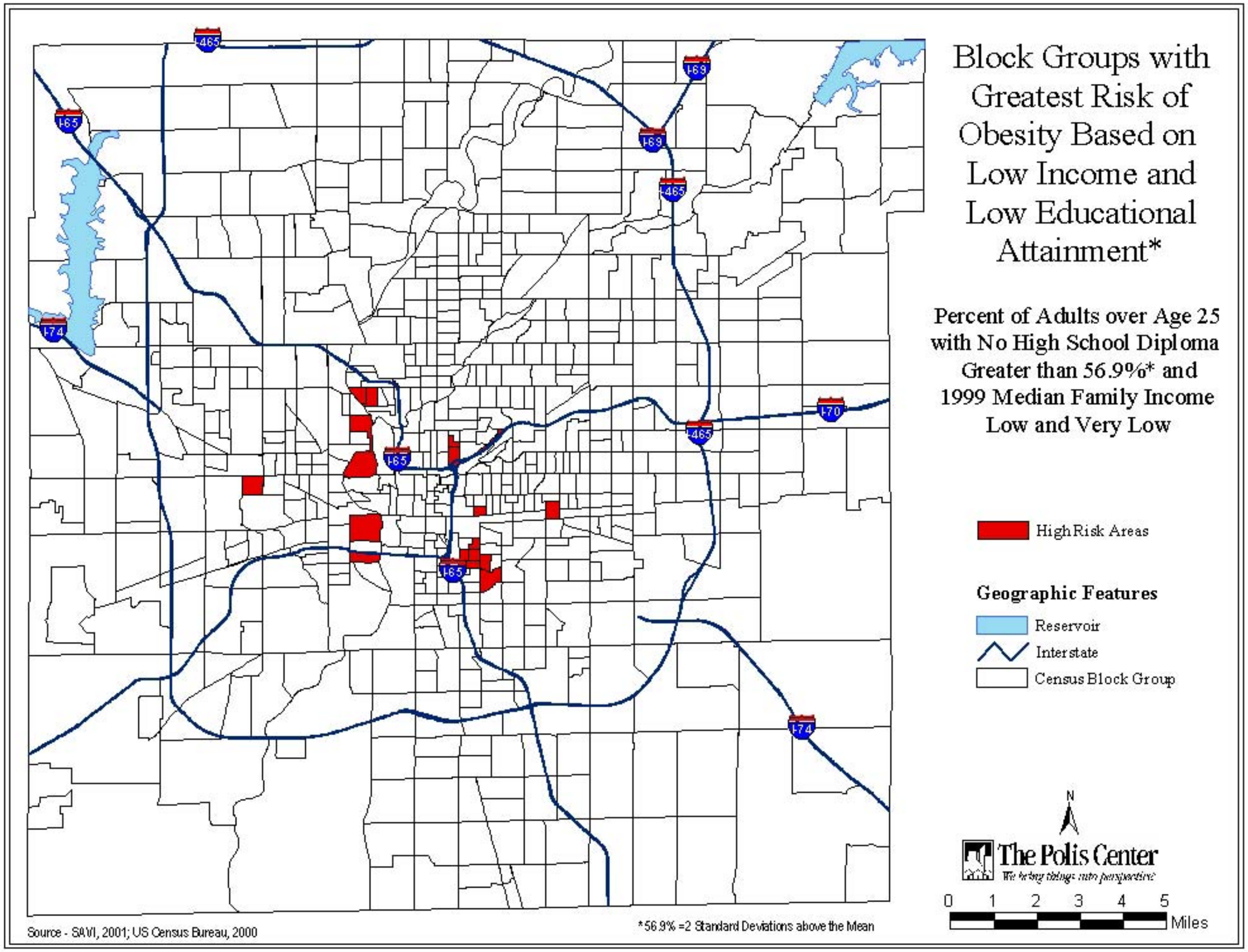
MAP 9: Highest Prevalence of Obesity and Educational Attainment



MAP 10: Lowest Prevalence of Obesity and Educational Attainment



MAP 11: Areas with Greatest Risk of Obesity Based on Income and Educational Attainment



APPENDIX C: REFERENCES

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APPENDIX D: STUDY CHALLENGES

The application of geographical information systems to improving health care quality is an under-studied field and advancing methodolgy in this arena presents a study challenge. We have grappled with questions concerning data accuracy and generalizability, as well as the feasibility of using GIS for health surveillance.

The pediatric data in the RMRS reflects a population in which African Americans, Latinos, and patients receiving Medicaid are over-represented. This selection bias, however, may work to our advantage given that several U.S. minority populations are disproportionately affected by obesity, particularly African Americans, Hispanics and Native American women.[69] Identifying environmental changes that either reinforce healthy eating and exercise or reduce the barriers to healthy lifestyles may diminish disparities related to obesity, as barriers may be more prevalent in ethnic minority groups or disadvantaged communities.

Challenges

Data

- Extracting data from the medical records system was a challenge. Specifically, the height and weight data resided in an unexpected repository, which resulted in skewed data (preponderance of females and older age groups) for the initial 5-year analysis.
- Unable to obtain permission to use TANF recipients by block group to measure "diet" at the time of this study due to staff changes
- Determined only to use % of population without a high school degree as an measure of educational attainment
- Unable obtain permission to use collect food stamp recipients by block group to measure "diet" at the time of this study due to staff changes
- Decided not to use Free or reduced school lunch because the school corporation unit is too large for this study (e.g. Indianapolis Public Schools corporation covers 20% of the county). Furthermore, we could not determine which school each patient attends, so there was no way to link the school-level data to the subjects. Aggregating these data by block group resulted in clusters where the school is located.
- Determined only to use violent crime rate as a measure of high crime areas.
- Defining meaningful income classifications was a challenge of the study.
- Our study population is largely African American and has low socioeconomic status.
- Crime data only covers the Indianapolis Police Department service area, which is a portion of the county.
- At the time of the 1-year analysis, only 1990 census data were available.

Mapping

- Determining how to display the weight classifications against the various environmental variables was very difficult due to the large number of study subjects and small size of study units (census block groups).

Collaborators

- Difficult bringing the large group of collaborators together, including The Polis Center, The Diabetes Research and Training Center, The Children's Health Services Research Program, and The Division of Biostatistics. Complications with coordinating the collaborators' schedules resulted in difficulty establishing and meeting project target dates.