Socioeconomic Disparities, Community Physical Environment, and Childhood Obesity in Alabama's Black Belt Region

by

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Abstract

Health inequalities have been linked to socioeconomic disparities. These disparities are communal differences which have a profound influence on the physical environment. Scholarship has recently connected socioeconomic disparities with obesity, a current epidemic in many nations that disproportionately affects those from racial and ethnic minority groups as well as those from a lower socioeconomic status. The issue is particularly important in the Black Belt region of the rural South, where counties are characterized by high percentages of African American population and prominent rates of poverty. Community physical environments can influence obesity rates through two components, the food environment and the physical activity environment. Both of these have an equally important impact on the health of a community, as the former describes energy intake while the latter describes energy expenditure. This research aims to focus on an understudied population, children from rural Black Belt counties, in order to evaluate obesity rates in relation to the surrounding physical environment. 664 children from five elementary schools in two Black Belt counties were analyzed to more comprehensively understand obesity among children in the rural Black Belt. This was accomplished through the use of mixed methods, quantitative measurements acquired through GIS techniques and statistical analysis and qualitative measures derived from survey questionnaires and spatial video recordings of the physical environment.

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1. Introduction

Recent studies concerning the health of populations have shown that health inequalities within communities have been linked to socioeconomic disparities (Cromley, 2003; McLafferty, 2003). Socioeconomic disparity refers to the communal difference in social and economic measures such as racial/ethnic groups, education level, and income level which have a profound effect on the existing status of health within a community as well as a direct influence on the physical environment (Darden, Rahbar, Jezierski, Li, & Velie, 2010). Importantly, scholarship has more recently connected these socioeconomic disparities with obesity, an issue verging on epidemic levels in many nations (Bogle & Sykes, 2011; Franzini et al., 2009; Smith, Cummins, Clark, & Stansfeld, 2013). In the United States, minority and low socioeconomic status (SES) populations have limited opportunities to participate in physical activity (Gordon-Larsen, Nelson, Page, & Popkin, 2006). Low participation in physical activity translates to a sedentary lifestyle that contributes to an increased risk of obesity in disadvantaged communities. This disproportionate result is particularly visible in the rural South, where in some counties, over half of the school children are overweight or obese (Tovar et al., 2012), contributing to an increased risk of chronic diseases compared to other children across the United States (Davy, Harrell, Stewart, & King, 2004).

The physical environment can play a key role in obesity patterns (Gordon-Larsen et al., 2006; Casey et al., 2011). Previous research has suggested that there are both

positive and negative effects associated with a community's physical environment that can impact residents' weights. The term physical environment is favored in this research over the more commonly used term built environment, because this research encompasses variables derived from both the built and natural environment. A disadvantageous physical environment may impede energy expenditure and increase energy intake, or an advantageous physical environment may promote energy expenditure while providing better energy intake options (Oreskovic, Kuhlthau, Romm, & Perrin, 2009). This can be due to characteristics of the environment such as walkability (Smith et al., 2013), availability of physical activity sites (Franzini et al., 2009), and location of food stores (Casey et al., 2011; Dunn, 2010). The goal of this research will be to add to the existing literature concerning socioeconomic disparities associated with childhood obesity levels, and the degree to which an unequal community physical environment affects overweight and obesity measures for an underserved population of children in a rural environment, namely, the Black Belt region of Alabama.

The Black Belt is the regional name given to a crescent-shaped stretch of counties that run east-west across the mid-section of the southern United States, extending from southwest Tennessee into east-central Mississippi and across the mid-section of Alabama to the Georgia border. Previous research has found that areas of poverty tend to cluster together, and Alabama's Black Belt region is an example of this phenomenon (Wimberley & Morris, 2003). Though the term Black Belt originally refers to the dark prairie soil that underlies this region (Gibson, 1941), it coincidentally describes the racial makeup of the region as well with some counties having African American percentages as high as 80% (United States Census Bureau, 2012). Because SES and health disparities

are influenced by poverty, the Black Belt serves as an excellent study area to examine the effects of these disparities on rural African American children. This study will focus on two Black Belt counties located in Alabama.

Disparities in health have previously been linked to physical environments, most notably to food environments (Smith et al., 2013) and to physical activity (PA) environments (Casey et al., 2012). The term food environment refers to the quantity and quality of available foods in a particular communal environment (Moore, Roux, Nettleton, & Jacobs, 2008). Previous attempts to model the food environment have consisted of measures such as participant-reported reviews of local food options, qualitative observations of available foods, and densities of particular food store types like supermarkets, grocery stores, and fast food restaurants (Moore et al., 2008). Another measure of the physical environment includes the PA environment (Gordon-Larsen et al., 2006). Previous research efforts attempting to model the PA environment have included locational variables such as public and private exercise facilities, parks, schools, and youth organizations (Gordon-Larsen et al., 2006). Also, density-based variables such as street-connectivity, dwelling density, and land-use diversity have been implemented (Witten et al., 2012). However, disparity in physical environments (both food and PA environments) is often associated with urban communities where significant variation exists in the landscape and is more easily identified than in rural communities.

In order to relate food and PA environments with individual and communal statistics and demographics, advanced methods must be implemented. Original attempts primarily consisted of geocoding addresses of individuals, food stores, and physical activity sites. Buffers are drawn around individuals and merged with properties of the

physical environment through means of geographic information systems (GIS) in order to measure accessibility to food stores and PA locations. This however is a measure based solely on buffer-distance applying arbitrary boundaries to our living space. Absolute physical distance alone is merely one aspect of measuring accessibility and is not fully representative on its own. Because these buffers represent our living spaces, a problem arises with communities of differing population densities. For example, urbanites are far less likely to travel the distances that rural-dwellers must travel in every-day life in order to obtain food and participate in recreational PA. Zhang et al. (2011) developed a measure known as Population-Weighted Distance (PWD) that measures how far residents of the United States must travel (network distance) in order to reach the nearest park, a common source of leisure-time PA for many individuals. Research has also taken a qualitative approach to obesity studies, where surveys can be used to reveal data that quantitative measures simply cannot. For example, the most proximate food or PA location might not be the most desirable to every individual. Personal preference will result in individuals traveling to specific food and PA locations based on more than just distance. Other qualitative measures recently implemented into geographic studies include the use of spatial video recordings, which can more accurately model a spatially continuous environment (Lewis, Fotheringham, & Winstanley, 2011). Spatial video allows multiple researchers to review and assess visual characteristics of the environment that promote or hinder the food and PA environment.

Limitations associated with existing obesity literature include the following three aspects: (1) a vast majority of existing literature concerned with environmental effects on health focuses on urban populations (Liu, Wilson, Qi, & Ying, 2007; Grow et al., 2010;

Smith et al., 2013) with little attention given to rural environments; (2) in the United States, unequal community physical environments have been documented; however, the research findings on the relationship between community physical environments and obesity rates are inconsistent (Holsten, 2008); and (3) many previous assessments of the environment in relation to health have included either quantitative or qualitative data analysis, where increasingly we are seeing that the uniqueness of individual communities requires a more comprehensive approach through the use of mixed methods (Matthews, 2012). Rural environments warrant attention and this study will serve the purpose to address this gap in obesity literature.

This research aims to examine an understudied population group, low-income rural African American children in the unique Black Belt region; to quantify the community physical environments; and to examine the complex interactions between socioeconomic disparities, community environments, and childhood obesity. Based on previous research studies, three primary hypotheses will be examined, (1) Black Belt region children experience higher rates of obesity compared to national averages, (2) community physical environments contribute to the high risk of overweight and obesity in rural southern children, and (3) community social environments also contribute to the high risk of overweight and obesity in rural southern children. This analysis will be done through the assistance of GIS tools and techniques as well as statistical analysis. The dependent variable of this research will be children's weight status indicated by percentile of body mass index. The independent variables include compound indices reflecting community food environments, physical activity environments, and individual-and community-level demographic indicators such as race, gender, age, and income.

2. Literature Review

This section will look to previously completed works in order to understand established theories behind health inequalities, how unequal physical environments (namely physical activity environments and food environments) can affect obesity rates, and how previous applications of Geographic Information Systems (GIS) have been implemented to understand spatial patterns of obesity.

2.1 Theoretical Pathways of Health Inequalities

Numerous preceding studies have examined the relationship between socioeconomic disparities and health inequalities. Currently, there are two well-accepted theoretical pathways by which to view health disparities in a more comprehensive manner, the psychosocial interpretation and the neo-material mechanism.

The psychosocial interpretation places focus on one's psychological development in relation to a surrounding social environment. This can be thought of as social interaction. For Richard Wilkinson (1996), one of the most-cited proponents of the psychosocial pathway, perception of place in the social hierarchy is a self-observed quality most heavily influenced by one's income. This self-perceived position in society can lead to positive or negative emotions, depending upon one's perceived place in society. Positive emotions can yield beneficial results to health just as negative emotions may result in stress-related behaviors degenerative to health, such as smoking, drinking, and use of drugs. Negative emotions like distrust can lead to deteriorative health, as it can

cause both physiologic reactions that are detrimental to our "internal" health as well as outward behaviors like anti-socialism that affect our "external" health (Lynch, Smith, Kaplan, & House, 2000). This individual view of oneself in relation to the surrounding social environment leads to what Wilkinson (1996) deemed as social cohesion, the participation and involvement in public affairs. Here, social cohesion, which can be quantified by measures such as voter participation or community involvement, was found to be a prominent factor when examining both health and income disparities. Our social relations have the ability to affect our health. The ideas behind the psychosocial pathway provide groundwork by which to view health disparities, yet the theory fails to acknowledge the material conditions and structural surroundings of a community that inevitably affect citizens living within a particular community.

The neo-material mechanism places focus on the material resources of a community and the existing macroeconomic conditions in relation to health inequalities (Lynch et al., 2000). Material resources that would promote a healthy environment exist on both the individual level and the communal level. Individually, access to nutritious food, clean water, and proper shelter can aid in the effort toward a healthier individual. Those with greater access to material resources (and those who have the ability to accumulate these resources) will inevitably be put at an advantage over those with limited individual means. Communally, the surrounding physical environment can also play an influential role in health outcomes (Li & Wei, 2010). For example, a community with the ability to easily access a range of physical activity and recreational facilities, such as public walking trails or parks, will experience improved health outcomes over a community which has little or no facilities that promote health and physical activity, as

long as the population is willing and able to utilize these facilities. Historical, economic, cultural, and political processes at individual and communal scales influence the amount of private and public resources available to a community, resulting in an unbalanced neomaterialistic landscape. In the next two sections, literature concerning the physical environment will be explored to examine the effects of an unequal physical environment on both physical activity and dietary behavior, and how this in turn relates to the issue of childhood obesity.

2.2 Unequal Physical Environments: Physical Activity and Obesity

Obesity is a condition which results from a complex combination of numerous factors. One of the most important factors in successfully contesting this epidemic is the participation in the proper amount of physical activity (PA), as increased PA has been negatively associated with obesity in children (Franzini et al., 2009). Individually, exercise can greatly benefit a healthy lifestyle, but communities can also provide means by which citizens can unintentionally or unconsciously participate in increased PA, for example a more walkable community or a nearby park. Casey et al. (2011) concluded that inverse relationships can be found between weight and greater walkability of a community, as well as between weight and spatial accessibility to recreational PA facilities. Previous research has also identified the effectiveness of neighborhood parks, public green spaces, and mixed land use developments in the reduction of sedentary behavior and promotion of PA in children (Zhang et al., 2011; Liu et al., 2007). The existing literature remains conclusive on the existence of health disparities in unequal physical environments which either promote or hinder the opportunity to participate in PA. For example, the walkability of a community refers to the availability of sidewalks

and the assumption that one can walk to every-day locations, such as work or grocery stores, or to a mode of public transportation, such as a subway or bus line. Here, reliance on walking and not on driving is emphasized in order to promote and increase activity, ultimately leading to a healthier lifestyle and reduced obesity rates. However, walkability studies have primarily been focused on urban areas where individuals are able to walk to the grocery store, to work, or to transportation lines. The diversity of land uses within an urban area makes it possible to accomplish errands on foot, ultimately increasing the amount of PA in which the citizens of a community will participate.

Access to recreational PA facilities has also been a major focus of physical environment studies. The availability and accessibility to parks, playgrounds, walking tracks, trails, sports complexes, recreational centers, gyms, health clubs, and other facilities that provide opportunities to exercise or participate in PA translates to a healthier physical environment with the assumption that the availability of these locations will promote the use of these amenities by individuals within a community. Just as well as any constructed PA center, public green spaces provide an excellent opportunity for exercise, especially in children who often participate in semi-structured activities that would best be suited for an open field.

As stated earlier, racial/ethnic minority groups and low socioeconomic status (SES) children are disproportionately affected by obesity rates and this holds true for the physical environment as well, where racial/ethnic minorities and lower SES groups are subject to living in disadvantageous physical environments that offer little opportunities for a healthier lifestyle, compounding the health disparities that already exist. According to Casey et al. (2012), children living in low-income neighborhoods have lower

accessibility to PA centers than do children living in wealthier neighborhoods, and these relationships are affected by individual and environmental socioeconomic characteristics. And Oreskovic et al. (2009) found that the physical environment can vary based on community income with wealthier individuals residing in a more advantageous physical environments. This results in children living in low-income areas which have physical environments that decrease the opportunity for energy expenditure.

Female children are another group that could be affected by participation in physical activity. Previous researchers examining the differences in physical activity among youth boys and girls have found that boys were more active than girls (Trost et al., 2002). Though the overall time spent participating in PA ultimately was equal between two genders, boys were more likely than girls to participate in more vigorous PA leading to increased aggregate amounts of PA. Other researchers have also identified the gap among genders in amount of time spent participating in vigorous PA (Van Mechelen et al., 2000; Fuchs et al., 1988). Self-reported and observational measures of physical activity participation also revealed a gender difference, with higher amounts of activity observed in males (Baranowski et al., 1993). Frequency variances in PA participation could be due to observed differences in participation in organized sport (Vilhjalmsson & Kristjansdottir, 2003). Regardless of the reasons for gender differences in participation of vigorous PA, previous studies have highlighted the potential need for intervention among young females to highlight the importance of participation in enough vigorous PA.

When discussing childhood obesity in relation to physical activity, focus is placed on energy expenditure. With obesity-related research, in conjunction with energy expenditure, we must also consider energy intake. In the following section, literature will be examined concerning dietary behaviors as they relate to the physical environment and the disparities that exist in food environments that can ultimately lead to childhood obesity.

2.3 Unequal Physical Environments: Dietary Behavior and Obesity

Just as important as the participation in proper amounts of physical activity (energy expenditure), so too is the adoption and implementation of healthy eating habits, including consuming the proper types and amounts of food (energy intake). In a modern day where efficiency and convenience seemingly dominate our behaviors and motivations, consumers have made a shift towards the purchasing of cheaper and more convenient foods, often which are those with high calorie, fat, and sugar contents. These purchasing patterns have become embodied in the landscape resulting in food environments that offer a multitude of fast food options and convenience stores with fewer opportunities to purchase healthy food items. And previous research has suggested that the type and location of food stores can influence our decisions to patronize those locations (Oreskovic et al., 2009; Casey et al., 2011; Moore et al., 2008). For example, Oreskovic et al. (2009) found that density of fast food restaurants was positively associated with overweight and obesity rates, while Casey et al. (2011) found a positive relationship with convenience stores. On the other hand, Moore et al. (2008) found that density of supermarkets translated to a healthier diet. This can lead to a categorization of the food environment into different types of food stores based on the assumption that certain types of food locations (i.e. fast food and convenience stores) will offer less healthy food options than other types of food locations (i.e. supermarkets).

Rural areas are put at a particular disadvantage when it comes to the food environment, where convenience stores and fast food locations dot the sparse landscape at crossroads to accommodate those traveling much longer distances than those in urban areas must travel to obtain food. Oreskovic et al. (2009) found that physical environments vary by town income, leading to the inference that socioeconomic disparities will play a role in producing diverse food environments. Rural areas, and specifically the Black Belt of Alabama, are often characterized by severe poverty and therefore limited in their economic opportunities. The availability of certain types of food stores is directly affected by this economic disparity. Large chain supermarkets that have the ability to sell quality fresh foods, like produce and meat, at a low price due to an economy of scale will not thrive economically in a rural environment with populations too low to support such large operations. This gives way to small "Mom-and-Pop" convenience stores that offer a limited selection of higher-priced and often less nutritious items. In one study of a rural county that identified quantity and quality of food locations, 74% of food stores identified were convenience stores, as opposed to 26% being supermarkets or grocery stores where the availability of healthier food items was found to be substantially higher (Liese, Weis, Pluto, Smith, & Lawson, 2007). Other studies have also noted the difference in prevalence of certain types of food stores based on the socioeconomic landscape of a community. Supermarkets occur much less frequently than convenience stores in high minority areas (Sloane et al., 2003). Also, food that was available for purchase at both supermarkets and convenience stores was priced substantially higher in convenience stores. This can give way to the assumption that convenience stores offer less healthy, more expensive food items compared to their supermarket counterpart.

2.4 The Applications of Spatial Analysis and GIS in Childhood Obesity Research

If previous research attempts have shown that overweight and obesity rates have a direct association with food and physical activity environments (Casey et al. 2011; Zhang et al. 2011; Oreskovic et al. 2009), then we can claim that this epidemic of childhood obesity is inherently geographic. Spatial analysis of geographic phenomena dates back as early as 1854 to the maps of Dr. John Snow drawn to record the outbreak of cholera in London. Since its infancy, spatial analysis and specifically geographic analysis of spatial phenomena has advanced into a robust study based on highly complex statistical calculations that deal with data which are just as intricate. To demonstrate the complexity of spatial data, consider this proposed research which will study the effects of physical environments on overweight and obesity rates. These rates have been shown to be a result of surrounding physical environments that play a role in influencing PA participation and dietary behaviors, two key components in obesity research (Casey et al. 2011; Zhang et al. 2011; Oreskovic et al. 2009; Moore et al. 2008). However, directly relating these environments to individual and communal demographics is a complicated and tedious process. Previous scholars have implemented modern techniques using geographic information systems (GIS) to model and potentially understand the complicated PA and food environments. For example, Zhang et al. (2011) developed a measurement know as population-weighted distance (PWD) in order to demonstrate the variation of network distances that people must travel to parks in the United States, based on their home location. PWD results ranged from 0.49 in urbanized areas (average number of miles that citizens must travel to reach the nearest park) to a whopping 599 in the most rural of counties.

Previous attempts to understand the physical environment in relation to obesity have considered measures such as density of and distance to PA locations and food stores. However, this implies that our living space is arbitrarily defined as some type of distance around a point where we are located, typically being home or work. Immediately, an alarm rings and the difficulty of this examination is identified. The assignment of a "living space" will always be wrought with complications. This leads to the application of the first law of geography, most commonly referred to as the distance decay model. According to Waldo Tobler (1970), the influence of a geographic phenomenon (in our case a food location or a physical activity site) decreases with increasing Euclidean distance. In other words, the closer a food location or PA site is to one's living space, the more influence it will have on an individual (i.e. a consumer will frequent food locations and PA sites which are nearby home and work locations). In the instance of childhood obesity research, children are most influenced by their environments surrounding home and school (Casey et al., 2011; Smith et al., 2013). By mapping home and school locations, a modified version of the distance decay model can be applied to help assess a spatially continuous food and PA environment.

The distance decay model is logical, however patrons do not always choose the closest option when deciding on a food store or an exercise location. A more complex model must be implemented that takes into account more than just distance. In 1931, William J. Reilly proposed his Law of Retail Gravitation (Reilly, 1931), a mathematic formula which attempted to calculate the bifurcation point where customers will be drawn to one of two competing retail areas. In addition to distance, this theory took into account the size of two competing centers, where the larger retail area will produce a

greater attraction, increasing the overall distance that patrons are willing to travel. However, this model separated trade areas into distinct indivisible units, and implied that two larger cities are competing for the influence on an intermediate city. In 1963, David L. Huff proposed his method for modeling patronization options within a particular trade area (Huff, 1963). Certain retail locations (which can belong to multiple trade areas) will influence surrounding individuals based on size and distance in relation to other similar options. This model does not focus on multiple distinct trade areas like Reilly's Retail Gravitation model. Instead, multiple outlets within a particular trade area are analyzed to determine their influence within the single community. GIS methods can be implemented to map the locations of food stores and PA sites, and spatial analysis can be conducted using a version of Huff's Model.

The use of GIS in health care and disease studies has gained steam within the last decade as researchers have been urgently trying to understand the relationship between spaces and the resulting pathological factors and health disparities (Cromley, 2003; McLafferty, 2003). Specifically, GIS can be used to examine the relationship between weight rates and accessibility to food locations and physical activity sites. This research will implement GIS in order to map weight rates in relation to accessibility to food stores and physical activity sites.

3. Methodology

3.1 Study Area

The study area consists of two counties within Alabama's Black Belt Region (Figure 1). Because the targeted population consists of children from low-SES areas, the counties involved are not named in order to de-identify participants as much as possible. The two counties were selected because of their primarily rural landscape, high poverty rate, low median household incomes, and high minority population (predominantly African American). Though both counties each have one defined urban cluster, the majority of both counties is defined as rural. Urban clusters are defined by the US Census Bureau as an area with a population ranging from 2,500 to 50,000 people. This is one step below the definition of an urbanized area which is defined by an area of 50,000 or more people, and one step above a rural area which is defined as an area of less than 2,500 people (United States Census Bureau, 2010). In 2010, the populations of the two counties were 21,452 and 52,847. Percentages of African American populations for the two counties respectively were 83.1% and 42.2%, compared to a statewide average for Alabama of 26.2%. Median household incomes (MHHI) for the two respective counties were \$27,957 and \$33,591 compared to a statewide average for Alabama of \$43,160. And poverty rates for the two counties respectively were 28.1% and 22.2% compared to a statewide average for Alabama of 18.1% (United States Census Bureau, 2010). Though the two counties are somewhat different in population and racial makeup, they both serve

as rural counties that could potentially highlight childhood obesity differences among juxtaposing groups, for example high vs. low SES, urban vs. rural, and majority vs. minority races/ethnicities.

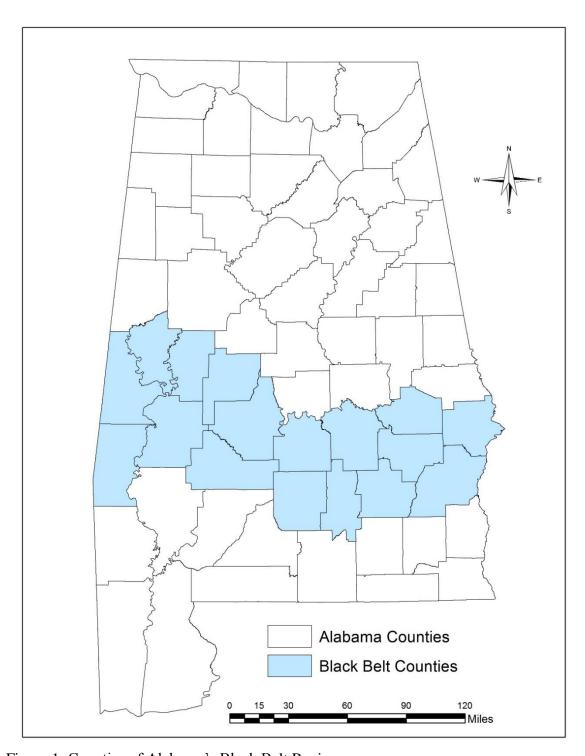


Figure 1: Counties of Alabama's Black Belt Region

3.2 Conceptual Framework

This study applied mixed methods in order to investigate the effects of rural disadvantageous physical environments on childhood obesity rates. The decision to observe children is based on the theory that healthy lifestyle decisions adopted at an early age could carry over into adulthood, essentially resulting in a future population with reduced obesity rates. Figure 2 illustrates the analytical framework that this research followed. The dependent variable was represented as percentile of BMI (BMI%). In attempt to wholly understand the environmental factors that affect childhood obesity, four primary components of the physical environment were analyzed, namely the physical activity environment, the food environment, individual demographics, and community demographics to observe how each of these four legs contributes to obesity. Figure 2 lists each of the four environmental components as well as individual measures used to describe each pathway.

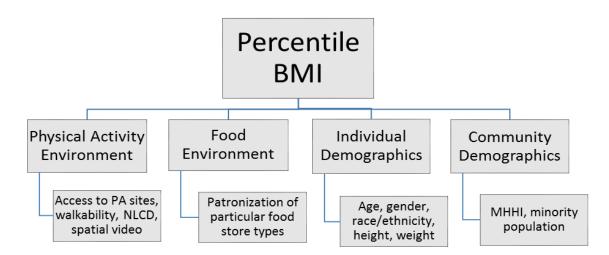


Figure 2: Analytical flowchart describing the pathways by which to observe percentile of Body Mass Index (BMI)

3.3 Data and Data Sources

To carry out this study, four categories of data were obtained (Table 1). In order to assess the physical activity environment and the food environment, public online resources were utilized to identify the locations of both physical activity sites and food locations. The Yellow Book and its associated website www.yellowbook.com were the source by which these PA sites and food store locations were obtained. Ground-truthing was implemented to confirm the existence of those listed, and potentially identify some locations which were not listed. Aerial imagery obtained using Google Earth was also used to identify recreational areas not listed in the Yellow Book, such as school playgrounds, walking tracks, baseball fields, basketball courts, tennis courts, and other outdoor recreation spaces. Size of food stores (building footprint in square meters) was also obtained via Google Earth for input into Huff's Model. The addresses of the PA sites and food locations were geocoded within ArcMap using street shapefiles obtained from the United States Census Bureau's TIGER/Line shapefile database. These street shapefiles were also used to calculate street intersection density within ArcMap. Remote sensing data from the National Land Cover Database (NLCD) was obtained in order to identify select land use/land cover (LULC) categories.

Another measure of the PA environment, walk score, was obtained via the website www.walkscore.com. Walk score is a measure of a location's walkability from any street address, which takes into account the number of surrounding amenities, walk times to these amenities, and road metrics such as block length to produce a final walk score which can range from 0 to 100 (Table 2). This unique formula was developed by an advisory board made up of urban planning and environmental experts and has been

Table 1: Examples of data and data sources

Environmental Component	Examples of Data
PA Environment	PA sites (gyms, parks, playgrounds etc.) identified using yellowbook.com, intersection density, walk scores, NLCD, and spatial video data
Food Environment	Food outlets (convenience stores, fast food restaurants, full service restaurants, and supermarkets) identified using the yellowbook.com
Individual Demographics	Individual data collected via survey: age, gender, race/ethnicity, weight, and height
Community Demographics	Communal data obtained from the US Census Bureau: Median household income (MHHI) and percentage of African-American population (both at block group level)

Table 2: Walk Score ratings and descriptions

Walk Score	Description
90-100	Walker's Paradise: daily errands do not require a car
70-89	Very Walkable: most errands can be accomplished on foot
50-69	Somewhat Walkable: some errands can be accomplished on foot
25-49	Car-Dependent: Most errands require a car
0-24	Car-Dependent: almost all errands require a car

validated by leading researchers in the fields of urban planning, real estate, and public health (Walk Score, 2015). Spatial video recordings of the study area were also collected and analyzed. This allowed multiple researchers to view the same video recordings of the community environment and to qualitatively assess aspects of that environment that could not be immediately identified through aerial imagery of GIS techniques, such as the present condition of playground equipment at a school, or the quality of sidewalks throughout a neighborhood.

Communal data, such as median household income and percentage of African American population, was obtained from the United States Census Bureau at the block group level. In some cases, block group level data was unavailable for download. In these cases, tract level data was obtained and applied to all block groups which fell inside that tract. TIGER/Line files were also implemented in order to map communal boundaries and streets. Individual demographic data was obtained via surveys distributed directly to the student participants while in school. A more in depth description of the surveys and survey data collected will be covered in the next section.

3.4 Survey Measures

Because this research involves interaction with human subjects, proper consent was obtained from Auburn University's Institutional Review Board for the Protection of Human Subjects in Research (IRB) in order to protect the rights and welfare of research participants. A web-based Human Subjects Research Training program was completed prior to data collection through the Collaborative Institutional Training Initiative (CITI) at the University of Miami. Completion certificates for necessary modules can be seen in Appendix A. Also, proper assent from the participants and consent from a parent or legal

guardian was required for children to participate in this study. This form can be seen in Appendix B.

Survey data were collected from children ages 4-13 years in five elementary schools throughout the two counties in the spring of 2013 and spring of 2014. Consent forms were distributed for parental approval before data were obtained from the children. Survey data completed by the children during school hours included individual demographic measures such as age, gender, and race/ethnicity. Anthropometric measurements were obtained on-site upon the completion of surveys. Height and weight measurements were obtained using a SECA 769 Digital Column Scale with SECA 220 Height Rod. Height measurements were recorded to the nearest 0.1 cm and weight measurements were taken to the nearest 0.1 lb. These anthropometric measurements were used to calculate a Body Mass Index (BMI; kg/m²), which was then compared to an ageand gender-specific chart produced by the Center for Disease Control and Prevention (CDC) that specifies BMI percentile (Ogden et al., 2002). BMI percentile was calculated using the BMI Percentile Calculator for Child and Teen (English Version) available on the CDC's website (http://nccd.cdc.gov/dnpabmi/Calculator.aspx). The calculated BMI percentile for each child ultimately served as the dependent variable in statistical analysis. In accordance with the definitions of the CDC, those with BMI percentiles of 85% up to 95% were considered to be "overweight," while those with percentiles of 95% and above were considered to be "obese." All BMI percentiles under 85% were considered as "normal weight". No designation will be made for participants who were measured as "underweight" (less than the 5th percentile), because the nature of this research is to identify potentially obesogenic environments.

3.5 Assessment of the Physical Activity Environment

The physical activity (PA) environment has previously been measured numerous ways in attempt to quantitatively represent opportunities to participate in PA in a particular physical environment. Early investigations into the PA environment have been initially focused on areas in which to participate in recreational activity, such as parks, playgrounds, recreational centers, or sporting facilities (Casey et al., 2011). More recent attempts to model the PA environment have focused on transportation as well using measurements such as walkability and accessibility to public transportation systems (Sallis et al., 2006). Additionally, other studies have also included psychological measurements of a physical environment, such as a social neighborhood environment measure which attempts to model the social cohesiveness of a neighborhood (Matthews & Yang, 2010).

All of these considered, a combination of these methods was used for this research. The PA environment was modeled by identifying recreational PA sites and digitizing their locations using ArcGIS 10. A map was established of the available sites throughout the study area for which children have the opportunity to participate in PA (Figure 3), and PA site densities were obtained for each block group. A total of forty-two PA sites were identified and documented. PA sites consisted of city parks, public playgrounds, school playgrounds, a sportsplex, community centers, hiking trails, mountain biking trails, tennis courts, basketball courts, and baseball fields. No documentation of private exercise facilities (gyms, health clubs) was made due to the age of the participants involved in this research. Though elementary-aged children might frequent facilities such as an ice skating rink, mini-golf course, indoor climbing wall,

laser tag facility, or other child-friendly businesses that promote PA, no such facilities were found in the study area.

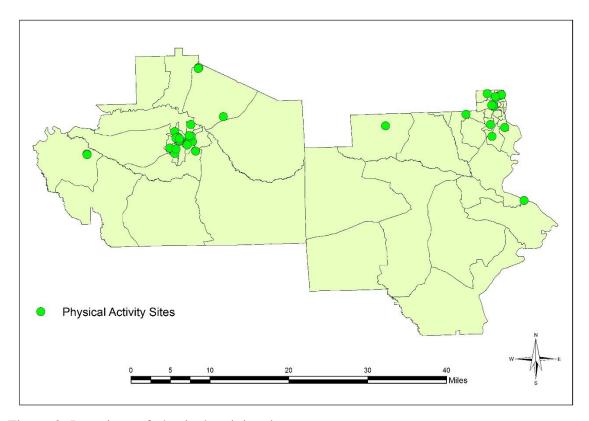


Figure 3: Locations of physical activity sites

Sallis et al. (2006) found that there was sufficient evidence to support the implementation of more walkable neighborhoods in order to increase PA. Walkability can be measured by variables like street intersection density, where a higher density leads to a higher probability that citizens will walk as their means of transportation (Witten et al. 2012). Walkability values were determined by examining the density of street intersections at the block group level. Street intersection density values by block group can be seen in Figure 4. A supplemental walkability value was obtained at the individual level (based on participants' home addresses) by utilizing the established formula from

www.walkscore.com. Identifying areas of poor walkability has important political implications that could help to reverse the sprawling pattern of today's cities by advocating for more walkable, and essentially healthier, neighborhoods.

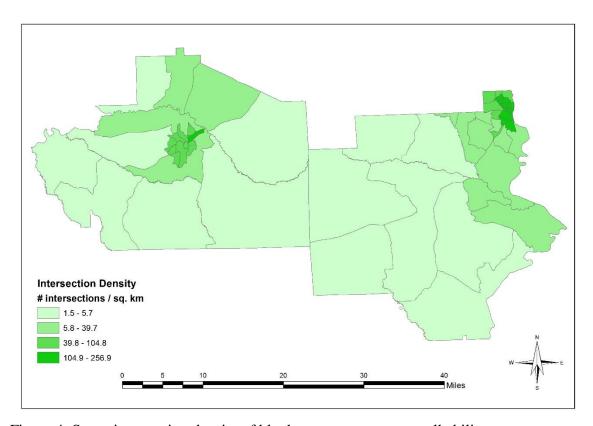


Figure 4: Street intersection density of block groups to suggest walkability

Finally, remote sensing data was obtained from the National Land Cover Database (NLCD) in order to identify four selected categories of land use/land cover: urban, grassland, forest, and agriculture (Figure 5). Physical environment research has highlighted the benefits of mixed land use and the walkability of urban areas (Casey et al. 2011). Also, increased amounts of vegetation in a community have been linked to lower rates in obesity (Liu et al., 2007). This research utilized NLCD data from 2011 to identify the land cover makeup of block groups throughout the study area. Land cover

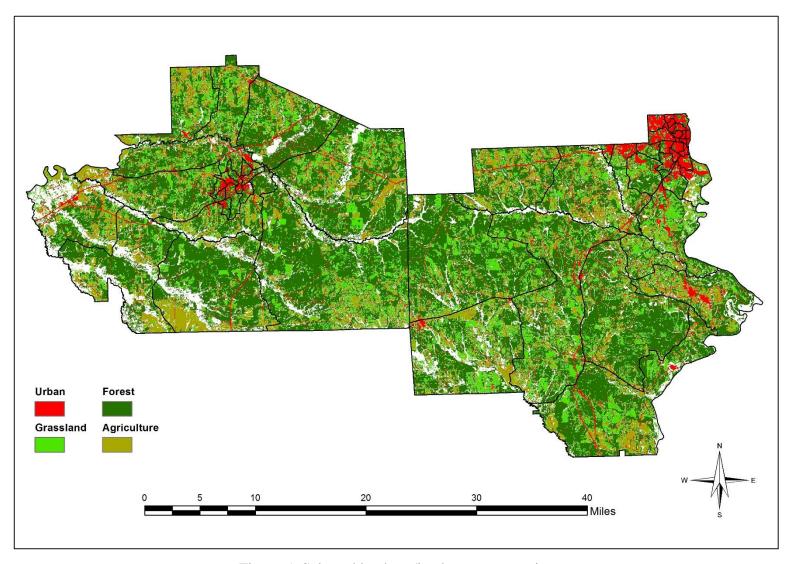


Figure 5: Selected land use/land cover categories

categories of interest served to highlight both urban areas (urban land cover) as well as vegetative areas (grassland, forest, and agricultural land covers) to identify the effect that these areas have on obesity patterns. Each of these four categories of land cover was extracted, and percentages for each category were calculated for all block groups.

Qualitative data assessing the condition of community PA environments was developed using geospatial video recordings captured by a Contour +2 GPS enhanced high-definition video camera. Geospatial video allows users to record videos of geographic environments all while maintaining accurate location data through an integrated GPS. Though this method is fairly new to data collection, it offers many advantages, such as archival of data for later review, efficiency and feasibility in data collection, and objectivity of data (Curtis, Mills, Kennedy, Fotheringham, & McCarthy, 2007). The use of geospatial video recordings also allows for users to be able to identify diverse environments (Mills, Curtis, B. Kennedy, S. Kennedy, & Edwards, 2010). By assigning qualitative codes to spatial environments, multiple researchers can review the same environment without actually having to see the environment in person themselves. For this project, diversity among PA environments was assessed through the use of geospatial video. The Contour +2 camera was mounted to the dashboard of a vehicle (Figure 6) while video and GPS data were recorded as the car drove across the study area. Figure 7 shows an example of how this data was processed using the camera's associated computer software, Contour Storyteller. The still image comes from the video recording while the real-time GPS points are translated onto an inset map in the top-right corner. This software allows for users to easily match GPS location to video data. The video data was reviewed by three graduate students and a code was developed based on analyzing

the content of the environment. In order to quantify the qualitative assessment, data were coded separately by three graduate students as either 1 (poor physical environment with little to no chance to participate in physical activity), 2 (fair physical environment with moderate opportunities to participate in physical activity), or 3 (good physical environment with above average opportunities to participate in physical activity). Codes were assigned to block groups within the study area. The final code for each block group was the average of the researchers' assessments.



Figure 6: Photo of Contour +2 geospatial video camera mounted to dashboard

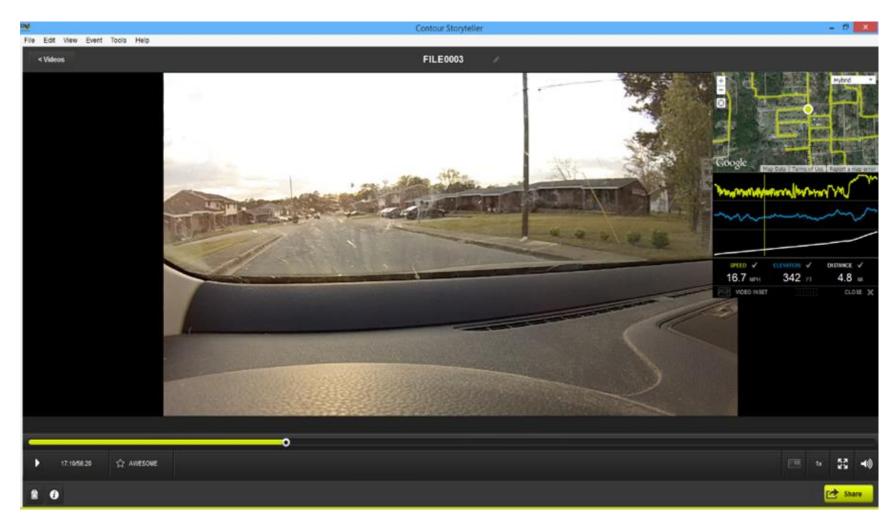


Figure 7: Screenshot example of geospatial video processing software

After all the PA environment data have been collected, an overall index measuring the PA environment at the block group level was developed based on a combination of all the variables. These variables include walk score, street intersection density, PA site density, vegetative land cover (agricultural land cover, grassland land cover, and forest land cover), urban land cover, and qualitative data acquired from spatial video recordings. All data was standardized by calculating z-scores using the following equation:

$$Z = \frac{X - \mu}{\sigma}$$

Z-scores were obtained by subtracting the mean score of the population (μ) from the raw score (X) and dividing by the standard deviation of the population (σ). Each block group has a z-score for all individual PA environment variables. The score reflects the rank of each block group in terms of the specific PA environment variable (Franzini et al. 2009). Each block group's z-scores of all PA variables were summed to result in an overall physical activity environment index (PAEI), where a higher PAEI represents a better environment for participation in PA and a lower PAEI represents a poorer environment for participation in PA.

3.6 Assessment of the Food Environment

The food environment has been previously modeled primarily based on either distance- or density-based measures that bring about problems of their own. Distance-based measurements assume that patronization of a food outlet is based solely on proximity. This ignores the attractiveness of some food stores which might offer a better selection or be cleaner than stores within a closer proximity. Density-based

measurements create problems as well by applying arbitrary boundaries to our livingspace by using a radial distance to measure stores that one might patronize. Distance
alone cannot be the measurement by which we assess accessibility and patronization, as
more attractive food options might be located outside of a radial living space assigned by
a researcher. Instead, this research followed the methods of Li et al. (2014) to model the
food environment. The adoption of Huff's Model, a well-established retail model, helped
to alleviate some of the issues that are present with distance- or density-based measures
of food stores. Huff's Model helps to identify the probability that children will patronize
a certain food location around their home or their school, based on the attractiveness of a
store in conjunction with Euclidean distance. This model takes into account all other food
options in the study area. Food stores located outside of the study area were not
considered. Though it is possible for residents to obtain food in neighboring counties, to
include such locations would venture beyond the logistical scope of this study. The
equation for calculating probability is as follows:

$$P_{ij} = \frac{(S_{j}/D_{ij}^{\beta})}{\left(\sum_{j=1}^{n} (S_{j}/D_{ij}^{\beta})\right)}$$

 P_{ij} is the probability that child i will patronize store j; S_j is the size of store j in square meters; D_{ij} is the Euclidean distance between child i and store j; β is a parameter (default = 2) assigned by the research team based on the effect that distance has when traveling to store j. The numerator gives a figure which represents the attractiveness of the store which is then divided by the sum of all other attractiveness measures.

This research included publically-listed stores which sell food that can be divided into one of four categories: convenience stores, fast food restaurants, full service restaurants, and supermarkets/grocery stores. This is based on previous research which identified particular types of food stores as selling particular types and qualities of food, with the assumption that convenience stores and fast food restaurants will offer a larger majority of high-caloric less healthy options while full service restaurants and supermarkets/grocery stores will offer more selections of healthier options (Dunn, 2010; Casey et al., 2011; Liese et al., 2007). The addresses for all food locations were obtained and input into a Microsoft Excel spreadsheet before being imported into ArcGIS 10 in order to geocode the addresses. Distances could then be obtained from food locations to the children's homes and school addresses for input into Huff's Model to obtain a probability that a child will patronize a particular food store. Because the two counties were treated as a singular study area, the closest food stores could have been located across county lines for some participants. Figure 8 shows the locations of all identified food stores. 127 total food stores were identified throughout the entire study area, fortyfive stores from one county and eighty-two from the other county. Fifty-six were convenience stores (44%), thirty-three were fast food restaurants (26%), twenty-five were full-service restaurants (20%), and thirteen were supermarkets/grocery stores (10%).

Just as an overall physical activity environment index was determined for each block group, so too will an overall food environment index (FEI). Each of the food stores identified was categorized as either a convenience store, a fast food restaurant, a full-service restaurant, or a supermarket/grocery store. The first two listed types of food stores offer less nutritious and higher-caloric food options, while the last two types of food

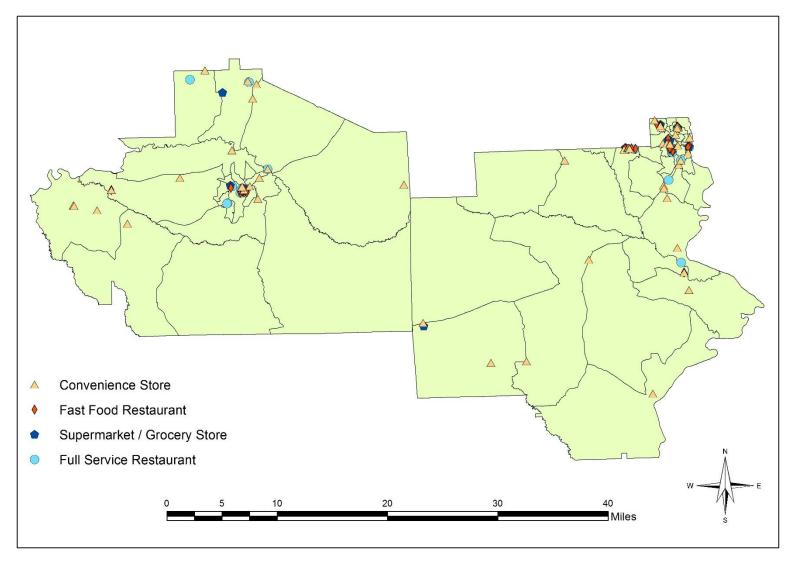


Figure 8: Locations of food stores

stores often offer more nutritious options. Probabilities of patronizing each food store were calculated using Huff's Model, and these probabilities were standardized using the same z-score equation as was used to standardize the PA environment data. In this situation, a higher z-score for a particular food store means that children will have a higher probability of frequenting that food store, whereas a lower z-score means children are less likely to visit that store. Because convenience stores and fast food restaurants represent unhealthy food options, higher z-scores for these locations would imply a higher probability of frequenting less healthy food options. Therefore, to account for the negativity of these locations and the detrimental effects they have to the food environment, original z-score from these two types of food stores were multiplied by -1. All z-scores for each particular category of food store (convenience, fast food, fullservice restaurant, or supermarket/grocery store) were summed to represent the overall probability that children will patronize a particular type of food store, painting a larger picture that goes beyond identifying probabilities to each individual store. This measurement will be known as the food environment index (FEI), where a higher FEI represents a healthier food environment and a lower FEI represents a more obesogenic food environment.

3.7 Statistical Analysis

Basic descriptive statistics were observed to identify any obesity patterns in individual demographics like gender, age, and race/ethnicity. This could highlight patterns of obesity in specific genders, races, age ranges and allow for intervention among at-risk groups. Community demographics such as median household income and percentage of African American population were also observed against obesity rates.

Additionally, schools which participants attended were observed as potential factors for affecting obesity rates.

Multilevel modeling was also implemented using MLwiN 2.20 statistical software produced by the Centre for Multilevel Modeling at the University of Bristol. This helped to examine the effects that PA environment and food environment variables (independent variables) have on percentile of BMI among participants (dependent variable). The independent variables summarized in Table 3 include variables from the PA environment, the food environment, individual-level demographics, community-level (block group) demographics, and school-level data.

The regression model attempted to identify how each of these individual variables affected percentile of BMI. Data was also organized into three hierarchical levels for the regression model: individual-level, block group-level, and school-level. This helped to account for the effects that block groups and schools have on participants. Schools were coded according to their distances from the urban cluster of the county to which they belong. This is due to the beneficial nature of urban settings which typically have better PA and food environments. The schools were coded as 1-5 with 1 being the closest school to the urban cluster and 5 being the school farthest away.

Table 3: Variables used for multilevel modeling

Variables	Categories	Specific variables	
Dependent	Weight Status	BMI Percentile	
	Food environment	Composite scores of probabilities that a child patronizes convenience stores	
		Composite scores of probabilities that a child patronizes fast food restaurants	
		Composite scores of probabilities that a child patronizes full service restaurants	
		Composite scores of probabilities that a child patronizes supermarkets or grocery stores	
	PA environment	Walk score obtained from walkscore.com	
		Street intersection density	
		Vegetative land cover	
Independent		Urban land cover	
		PA site density	
		Qualitative code from spatial video	
	Individual demographics	Age	
		Gender	
		Race	
	Communal demographics	Median household income	
		Percentage of African-American population	
	School Effects	School	

4. Results and Interpretation

4.1 Obesity Statistics on Selected Groups

Table 4 summarizes the basic obesity statistics on selected gender, age, and school groups. Out of 664 participants, 41.9% were measured as either overweight or obese. This is much higher than the national average of 31.8%, but is in line with the first hypothesis that Black Belt region residents experience higher rates of obesity compared to national averages. Many previous researchers have found health disparities, such as differences in obesity rates, to be linked to socioeconomic disparities (Tover et al., 2012; Franzini et al., 2009; Smith, Cummins, Clark, & Stansfeld, 2013). Also, previous research suggests the vulnerability of low SES populations, like that of the Black Belt region of Alabama (Bogle & Sykes, 2011).

If we first look to racial comparisons of overweight and obesity rates, participants involved with this study were primarily African American (93.2%), with only 5.5% identifying as White and 1.2% identifying as Other. African American and White children had respective overweight/obese rates of 42.0% and 40.5%, both well above the national average, and 50.0% of those not identifying as either African American or White were obese. Though previous research has suggested that racial minorities experience higher rates of obesity (Tovar et al., 2012), perhaps the reason for elevated overweight rates in White participants is due to the influence of the low-SES communities that make up the study area, as economically depressed areas tend to have higher rates of obesity in

Table 4: Sample obesity statistics for selected groups

	Group	Sample Size	% Overweight or obese
Gender	Male	322	41.3%
	Female	342	42.4%
	4-6	132	34.8%
Age	7-9	307	44.6%
1180	10-13	225	42.2%
School	1	364	42.9%
	2	83	37.3%
	3	43	34.9%
	4	72	45.8%
	5	102	44.1%
	Black	619	42.0%
Race	White	37	40.5%
	Other	8	50.0%
	Total	664	41.9%*

^{*}National average: 31.8%

comparison to financially thriving areas (Gordon-Larsen et al., 2006; Casey et al., 2012). However, no definitive claims should be made concerning racial differences in obesity in this study as there was not an even enough distribution among races/ethnicities to provide an accurate assessment.

If we look to the gender distribution, 41.3% of male participants were overweight or obese (BMI percentile of 85% and above) compared to 42.4% of females. Here, we find a similar rate with no significant difference between genders. Next, we can look to differences among obesity and overweight rates among age groups. Here, we have a drastically more stark contrast between groups than when observing gender differences. Only 34.8% of participants in the age range of 4 to 6 years were overweight or obese. This number increases sharply to 44.6% in the next age group of participants aged 7-9 years. After peaking in that age group, the number slightly decreases to 42.2% of participants aged 10-13 being overweight or obese. Previous research has highlighted a dramatic decrease in participation of PA among elementary aged children from first grade to sixth grade (Trost et al., 2002). Perhaps one of the more major contributors to childhood obesity could be the dramatic decrease in PA participation that exists as children age through elementary school. Other research has suggested the influential nature of biological processes, such as puberty, on weight gain, where children tend to lose control of their eating behaviors around early adolescence (International Association of Eating Disorders Professionals, 2014).

Lastly, we can also view the variances among overweight/obesity rates in different school populations. The schools were coded numerically as 1 through 5, with 1 being the school closest to the defined urban cluster and 5 being the school farthest away.

This is based on the assumption that urban environments offer better opportunities for PA participation and healthier food options as opposed to their rural counterparts (Tovar et al., 2012). We would then expect for School 1 to have a lower obesity rate and expect School 5 to have a higher rate. School 1 has an overweight/obesity rate of 42.9%, which is only slightly higher than the total population sampling (41.9%). However, this school has the largest sample size of 364 and nearly a totally African American population (99.7%). The large number of students from School 1 in relation to the overall sample could contribute to the closeness of School 1's overweight/obesity rates and the total population's overweight/obesity rates. Also, because minority races and ethnicities experience higher rates of obesity (Darden et al., 2010), this higher-than-expected value could potentially be explained by the racial makeup of the school. Researchers have also suggested correlation between community income and obesity rates, where low-SES communities experience higher obesity rates (Oreskovic et al., 2009; Darden et al., 2010). Among the participants that attend school at School 1, 65.7% live in block groups with median household incomes (MHHI) of less than \$25,000. This number was chosen as the break value due to \$25,000 being the approximate poverty threshold for a family of four (United States Census Bureau, 2014). This high percentage of participants living in impoverished areas could also contribute to the high overweight/obesity rate for School 1.

School 2 has an overweight/obesity rate of 37.3%, lower than the total population percentage. This is in line with the theory behind numerically coding the schools based on distance to urban clusters, where schools closer to those urban areas will experience decreased obesity rates. School 2 also falls in line with interpretations of our obesity data

in relation to age. School 2 only had participants in the age range of 4-6, which were found to have a lower overweight/obesity rate compared to older age groups.

School 3 has an even lower overweight/obesity rate (34.9%) than does School 2, and is well below the total population rate. However, just as School 1's racial and SES makeup could have affected their overweight/obesity rate, School 3's socioeconomic background could have affected rates in a positive way. 79.1% of the population from School 3 identified as White, with only 13.9% identifying as African American. Also, none of the participants live in a block group with a MHHI of less than \$25,000. In fact, the lowest MHHI of a participant from this school is \$31,293. The lower overweight/obesity rate for School 3 could potentially be explained by the racial and SES makeup of the community.

School 4 and School 5 can be explained under the scope of numerical coding, where these schools were expected to be the ones with higher obesity rates. Just so, these two schools have respective overweight/obesity rates of 45.8% and 44.1%, higher than the total population rate of 41.9%. Both schools had predominantly African American populations (93.1% and 100% respectively). In regards to MHHI of block groups in which the participants live, 41.7% of the participants from School 4 and 58.8% of the participants from School 5 live in block groups with MHHIs of less than \$25,000. However, it should be noted that none of the participants from either school live in block groups with MHHIs greater than \$27,284. This can contribute to research concerning SES differences in urban vs. rural populations, as participants living in the more rural, lower-SES areas of this study area experience higher-than-average obesity rates compared to participants living closer to the urban clusters of their respective counties.

4.2 Community Physical Environment Assessment: Physical Activity Environment Index

Previous research has identified the importance of physical activity in reducing obesity rates (Franzini et al., 2009) as well as the effect that environments can have on the participation in physical activity (Casey et al., 2011; Zhang et al., 2011). In this research, a measurement was created (Physical Activity Environment Index) in order to assess the physical activity environment based on a number of associated variables. These variables include walk score, street intersection density, PA site density, vegetative land cover (agricultural land cover, grassland land cover, and forest land cover), urban land cover, and qualitative data acquired from spatial video recordings. All data were standardized and summed for each block group to give an overall measurement of the PA environment. This data can be seen in Figure 9. A visual spatial pattern can be identified with a clustering of higher PAEI block groups clustered in the central urban area of the westernmost county and in the northeastern urban area of the easternmost county. Urban areas have higher intersection densities and will likely score higher on qualitative ratings of physical environment, and therefore would likely possess the highest PAEI values.

If we compare the PAEI values to community demographics like median household income and racial makeup, we begin to see a clearer picture that supports initial hypotheses of low-SES areas and high-minority areas indicating a more obesogenic environment. Table 5 and Figures 10 and 11 show these results. When examining the effects of racial makeup on the PA environment, two categories were created to represent either predominantly White block groups or predominantly African American block groups. Only 86 of 664 participants (13.0%) lived in block groups which contained an African-American percentage of less than 50%. However, of those

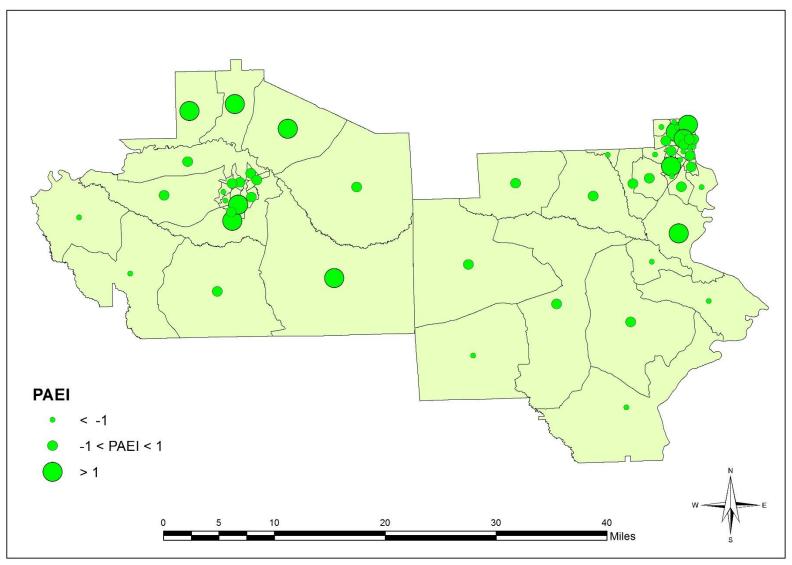


Figure 9: Physical Activity Environment Index (PAEI) for block groups within the study area

participants who lived in these block groups, 52.3% lived in a favorable PA environment (PAEI > 1), and only 10.5% lived in an unfavorable PA environment (PAEI < -1). If we examine the category of participants who live in block groups with African American percentages above 50%, a different result is seen. As opposed to non-minority block groups where one out of every two students lived in a favorable PA environment, only one out of every four (25.4%) students from the minority block groups lived in a favorable PA environment. Approximately the same amount (27.9%) lived in block groups with an unfavorable PA environment.

Table 5: PAEI in comparison to block group level demographics

% African American	Sample size	PAEI < -1	-1 < PAEI < 1	PAEI > 1
< 50%	86	10.5%	37.2%	52.3%
> 50%	578	27.9%	46.7%	25.4%
MHHI				
> \$25,000	281	18.9%	32.0%	49.1%
< \$25,000	383	30.5%	55.4%	14.1%

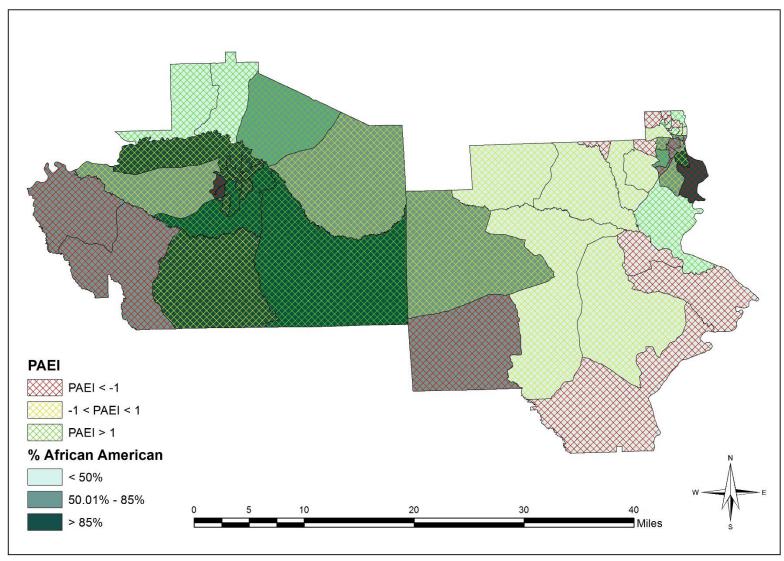


Figure 10: PAEI compared to racial makeup of block groups

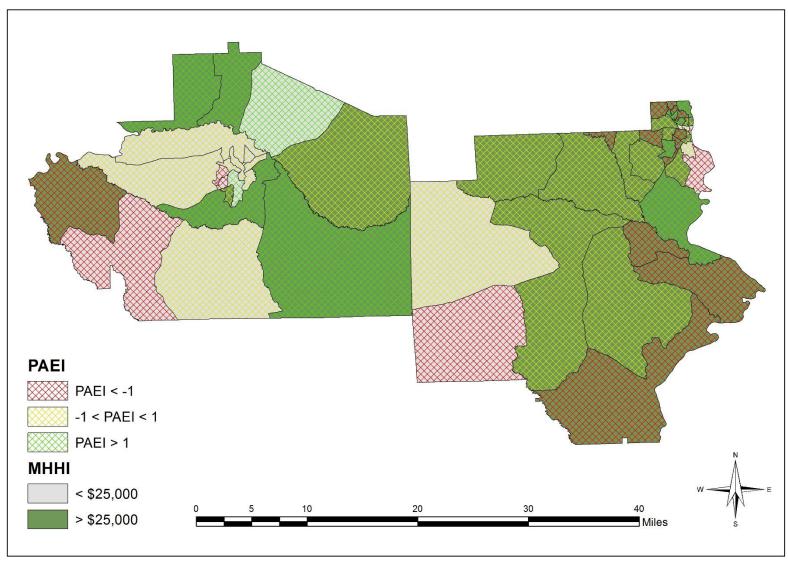


Figure 11: PAEI compared to median household income of block groups

Participants were also divided into two groups based on the median household income of the block group in which they live. The \$25,000 break point is the approximate poverty threshold for a family of four (United States Census Bureau, 2014). Here, we have a more even spread of participants among the two groups, but with a slight majority (57.7%) living in block groups below the poverty threshold. Of those living in these block groups, only 14.1% lived in a favorable PA environment with a PAEI > 1. Conversely, nearly one-third (30.5%) lived in an unfavorable PA environment with a PAEI < -1. Participants who lived in block groups with a MHHI > \$25,000 were much more likely to live in a favorable PA environment, with nearly half (49.1%) living in block groups with a PAEI > 1. Only 18.9% of the higher MHHI group lived in an unfavorable PA environment.

Table 5 supports previous research that has identified high minority and low-SES areas as obesogenic environments with minimal amounts of opportunity to participate in physical activity (Gordon-Larsen et al., 2006; Tovar et al., 2012). These results help to illuminate the differences of PA environments among communities of different racial/ethnic and SES backgrounds. Low-SES and high minority communities could be the best starting point for PA-based intervention and, perhaps, community improvement measures that allow for more opportunities to participate in PA.

4.3 Community Physical Environment Assessment: Food Environment Index

Childhood obesity research has often identified the food environment as a contributor to an obesogenic environment (Oreskovic et al., 2009; Casey et al., 2011; Moore et al., 2008). This research attempted to identify positive and negative food environments by first using Huff's Model to estimate the probabilities that participants

living within a particular block group will patronize certain types of food stores. Figures 12-15 show composite scores of probabilities that participants within a particular block group patronize one of four types of food stores: convenience stores, fast food restaurants, full service restaurants, and supermarkets/grocery stores.

The patterns of Figures 12-15 are somewhat expected. The probability that participants will frequent certain types of food stores is influenced by the distance to each type of food store. Therefore, because most of the food stores are clustered around the urban areas of both counties, we see a pattern of higher probabilities of frequenting all types of food stores within these urban areas. Composite probabilities were obtained for each of the four types of food stores, with full-service restaurants and supermarkets/grocery stores representing healthier food options, and with convenience stores and fast-food restaurants representing less healthy food options. Because the latter two food stores contribute to the availability of less quality food, their composite scores were multiplied by -1. All four composite probabilities are summed together for each block group to produce an overall Food Environment Index (FEI) which can attempt to model the food environment based on available selections of locations to purchase food. A higher FEI score represents a healthier food environment while a lower FEI score represents a less healthy food environment. Figure 16 shows these FEI scores by block group, with spatial clustering of high FEI scores around the urban clusters of each county.

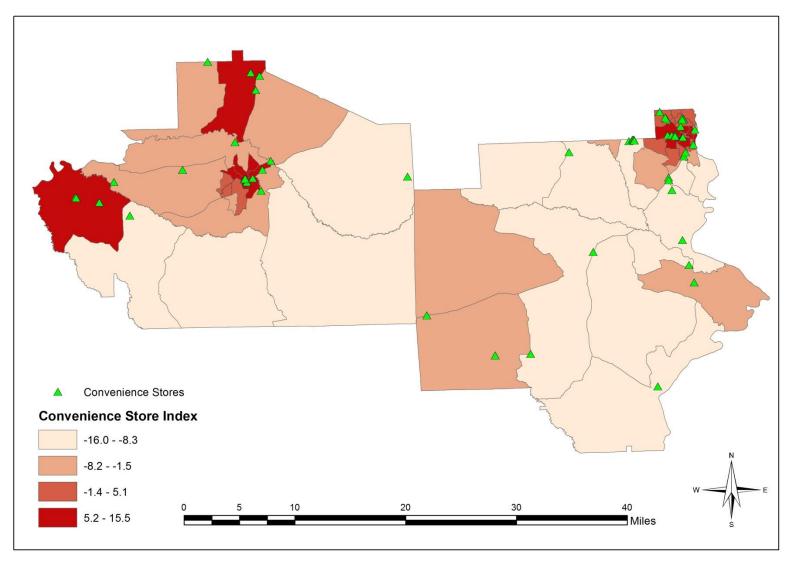


Figure 12: Composite index that participants will frequent convenience stores

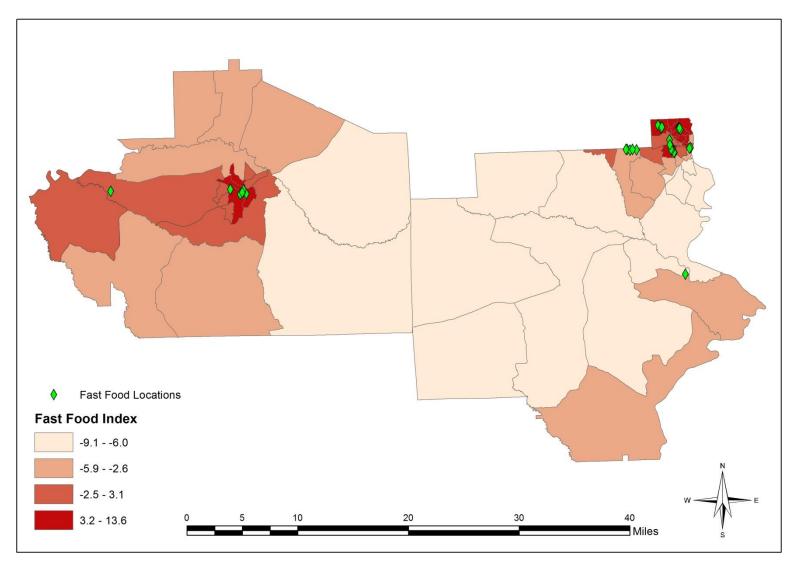


Figure 13: Composite index that participants will frequent fast food restaurants

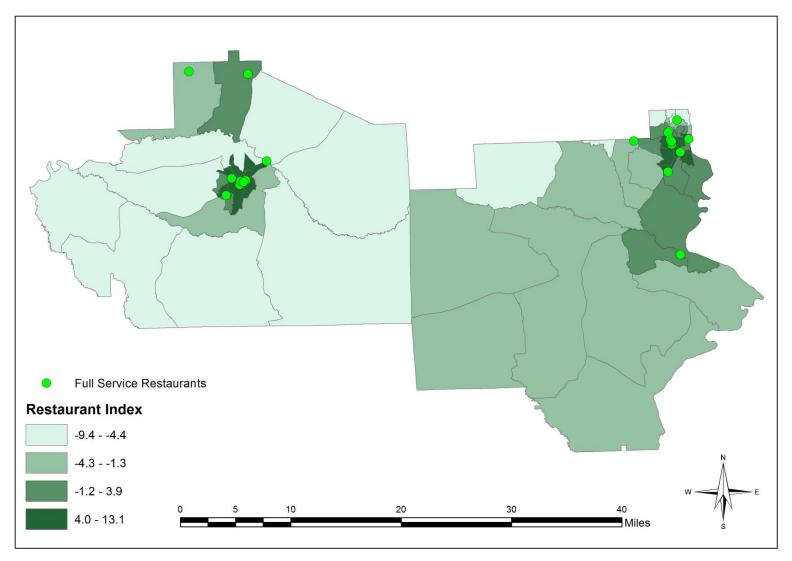


Figure 14: Composite index that participants will frequent full service restaurants

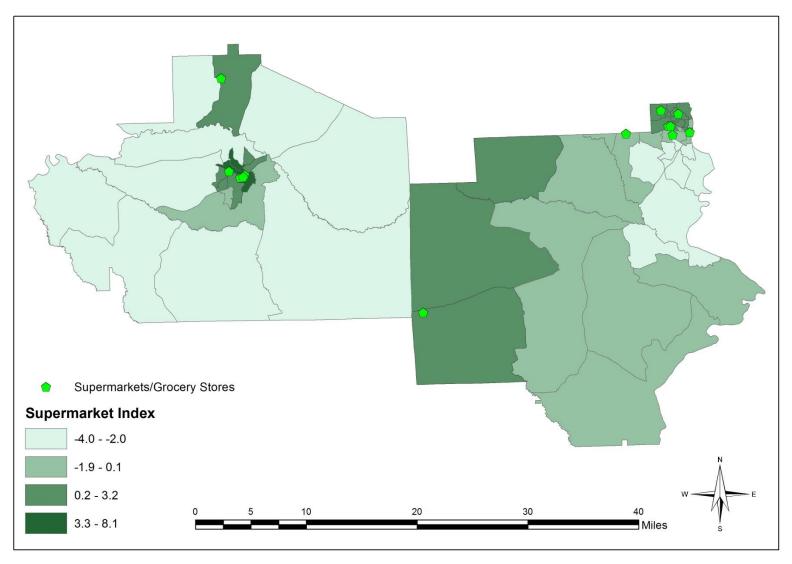


Figure 15: Composite index that participants will frequent supermarkets/grocery stores

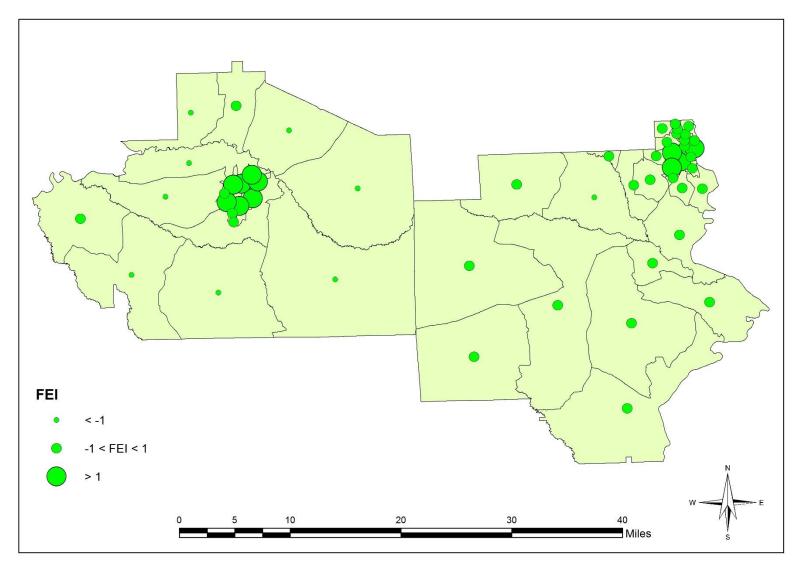


Figure 16: Food Environment Index by block group

FEI scores were compared to the same block group level demographics as were the PAEI scores, percentage of African American population and median household income, and are summarized in Table 6.

Table 6: FEI in comparison to block group level demographics

% African American	Sample size	FEI < -1	-1 < FEI < 1	FEI > 1
< 50%	86	47.7%	24.4%	27.9%
> 50%	578	37.9%	7.4%	54.7%
MHHI				
> \$25,000	281	29.9%	7.8%	62.3%
< \$25,000	383	46.0%	26.9%	27.1%

For participants living in block groups with African American population below 50%, nearly half (47.7%) were found to be living in block groups with a FEI < -1. Only 27.9% of these participants lived in a favorable food environment with a FEI > 1. However, when we examine block groups with African American percentages above fifty, an unexpected result is discovered. Over half of participants (54.7) living in predominantly African American communities were found to be living in favorable food environments with a FEI > 1. This is contradictory to previous research that has identified minority neighborhoods as having less healthy food purchasing options, for example more convenience stores and less supermarkets or less variety when purchasing food (Moore & Roux, 2006; Sloane et al., 2003). Higher FEI scores can be seen in Figure 17 concentrated around the urban areas, where the predominant race is African American. Therefore, the high FEI scores of block groups with African American percentages above fifty could be a byproduct of the high overall percentage of African Americans in the study area.

Table 6 and Figures 17 and 18 demonstrate some support and some contradiction for previous research and this research's assumptions of community effects on food environments. While median household income data aligned with previous research findings (lower MHHI areas having worse food environments), data concerning food environments in relation to racial composition of block groups was somewhat contradictory to assumptions that racial minority areas have worse food environments. However, this could be assumed only in areas where there is a more prominent racial mix of citizens, not in an area populated primarily by an African Americans as is the study area of this research.

Comparing FEI scores to median household income, we can see a more expected pattern mapped in Figure 18. 62.3% of participants residing in block groups with a MHHI > \$25,000 lived in a favorable food environment (FEI > 1), while only 29.9% lived in an unfavorable food environment (FEI < -1). Lower MHHI block groups also were found to have a higher instance of unfavorable food environments (46.0%), with only 27.1% living in favorable food environments.

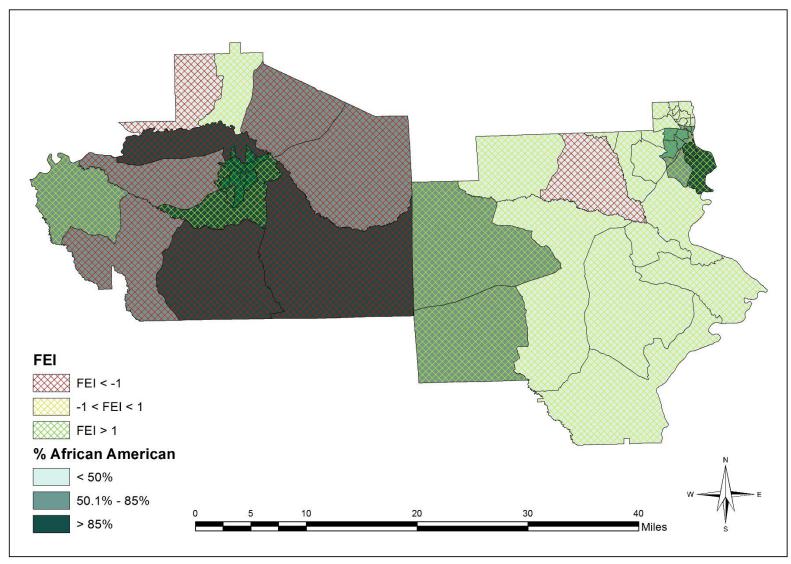


Figure 17: FEI compared to racial makeup of block groups

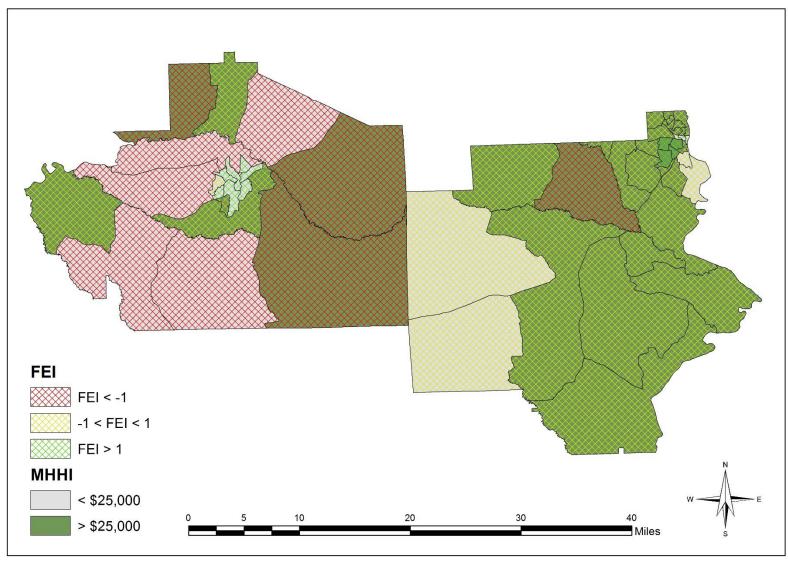


Figure 18: FEI compared to median household income of block groups

4.4 Results from Multilevel Modeling

The purpose of multilevel modeling was to examine the effects that a set of independent variables have on a dependent variable while accounting for the hierarchical nature the data being studied. For example, in terms of this research, data was sorted at three tiered levels, the individual level, the block group level, and the school level. All of these determine the particular physical environment to which participants are exposed. Two multilevel models were constructed to examine the effects that the PA environment and food environment have on BMI percentiles of participants respectively. Independent variables used to calculate the Physical Activity Environment Index and Food Environment Index will be used for each respective model to examine the significance and magnitude that each variable has on BMI percentiles.

4.4.1 Multilevel Modeling and the Physical Activity Environment

Table 7 shows the results of the first multilevel model examining the PA environment. Each independent variable has an associated coefficient and p-value. The p-value represents the significance value of whether or not the variable statistically contributes to the change in the dependent variable, while the coefficient represents a direction and magnitude to which the independent variable influences the dependent variable. The first variable listed is the block group average walk score. Because this value is significant and the coefficient is negative (p-value < 0.01; -5.85), the model tells us that lower walk scores lead to increased BMI percentiles. This is in line with associated literature which highlights the benefits of more walkable communities as healthier places (Sallis et al., 2006; Witten et al. 2012).

Table 7: Results of multilevel modeling for assessing PA environment and percentile of BMI

Independent Variable	Coefficient	p-value
Walk Score	-5.85	< 0.01*
Intersection Density	551.19	0.68
Vegetative Land Cover	1.99	< 0.05 [†]
Urban Land Cover	-21.84	< 0.01*
PA site Density	-11.56	< 0.05 [†]
Spatial Video	8.42	< 0.05 [†]
Percentage African American	0.24	< 0.01*
Median Household Income	-0.000034	0.48
School	2.12	< 0.01*
Age	3.94	< 0.01*
Gender	1.47	0.57
Race	9.24	< 0.01*

[†] Significant at the 95% confidence level * Significant at the 99% confidence level

Looking at the values from our land cover categories, the results reveal an interesting pattern. Higher amounts of urban land cover were significantly associated with decreased BMI percentiles (p-value < 0.01; -21.84), while higher amounts of vegetative land cover were significantly associated with increased BMI percentiles (p-value < 0.05; 1.99). Though previous literature has suggested the importance of both urban land cover and vegetative land cover in reducing obesity rates (Zhang et al., 2011; Liu et al., 2007), perhaps vegetative land cover in this specific study area implies a more predominantly rural area, as opposed to previous studies which identified vegetative land cover within urban areas themselves. In this case, it would be expected for rural areas to have a higher rate of obesity based on previous literature (Tovar et al., 2012).

Higher PA site density (p-value < 0.05; -11.56) was found to have a significant association with decreased BMI percentiles, where areas with more PA sites experience lower obesity rates. The results for spatial video (p-value < 0.05; 8.42) go against initial thinking in that this variable has a positive coefficient. A higher spatial video code should result in a lower percentage of obesity, however this model suggests otherwise.

Community demographic variables, school codes, age, gender, and race were added to the model to reveal the effects of block group level community data, school data, and individual data on obesity. Block groups with higher percentages of African American population were found to have increased BMI percentiles (p-value < 0.01; 0.24), but no significance was identified from median household income (p-value = 0.48). The school code was found to be significantly associated with increased obesity rates (p-value < 0.01; 2.12). Because schools were coded as 1-5 depending on their distance to the urban area of the county in which they are located (with 1 being the closest and 5 being

the farthest away), we found that schools farther away from urban areas experience higher obesity rates than those closest to the downtown areas. Our sample statistics from Table 4 suggested that as children age, their risk for being overweight or obese increases. This model supports those findings with increasing age being significantly associated with increased BMI percentiles (p-value < 0.01; 3.94). Although gender was not found to significantly affect BMI percentiles (p-value = 0.57), race proved to be a significant factor indicating obesity (p-value < 0.01; 9.24). African American children were given the lowest code, while White participants were given the highest code. This model suggests that African American children experience lower rates of obesity, however this result could be due in part to the lack of diversity among the population, where 93.2% of participants were African American.

4.4.2 Multilevel Modeling and the Food Environment

Table 8 illustrates the results obtained from the second multilevel model, which examined the effects that the community food environment has on BMI percentiles. The independent variables used were the same composite scores used to calculate the Food Environment Index. Fast food restaurants and convenience stores typically offer less healthy food options and contribute to higher obesity rates (Dunn, 2010; Casey et al., 2011; Liese et al., 2007). Therefore, we would expect higher obesity rates in areas where participants are more likely to frequent these types of food stores. The composite index of fast food restaurants was significantly associated with increased BMI percentiles (p-value < 0.01; 2.06) as would be expected. Just as well, convenience stores were found to have a significant correlation (p-value < 0.05; 0.38) with higher weights. Full service restaurants and supermarkets tend to offer healthier food options which could help to reduce obesity

Table 8: Results of multilevel modeling for assessing the food environment and percentile of BMI

Independent Variable	Coefficient	p-value
Fast Food	2.06	< 0.01*
Convenience Store	0.38	< 0.05 [†]
Restaurant	1.76	< 0.01*
Supermarket	-2.36	$< 0.05^{\dagger}$
Percentage African American	0.39	< 0.01*
Median Household Income	-0.000061	0.77
School	2.45	$< 0.05^{\dagger}$
Age	3.30	< 0.01*
Gender	-2.03	0.33
Race	8.23	< 0.01*

[†] Significant at the 95% confidence level * Significant at the 99% confidence level

rates for those participants who are more likely to frequent these types of stores (Moore et al., 2008). However, although supermarkets followed that trend (p-value < 0.05; -2.36), full service restaurants were significantly associated with increased BMI percentiles (p-value < 0.01; 1.76), contradictory to initial thinking.

Community demographic variables, school codes, and age remained in this model again to examine the effects of this data on weight rates and food environments. Just as in the PA environment model, percentage of African American population was significantly associated with increased BMI percentiles (p-value < 0.01; 0.39), and MHHI showed no significant correlation. The school which participants attended was found to have a significant correlation with increased weights (p-value < 0.05; 2.45). Schools with higher codes (those farther away from urban areas) were associated with higher BMI percentiles. Similar to the first model, increasing age also suggests significant correlation to higher BMI percentiles (p-value < 0.01; 3.30). Again, the results for gender and race were similar to the first model. No significant result was found in relation to gender differences and BMI percentiles (p-value = 0.33), while race proved to be significant in affecting obesity rates (p-value < 0.01; 8.23). Though this model, like the first, suggests that African American children experience lower rates of obesity, this could be due to the low percentage of non-African American participants within this study.

4.5 Summary of Findings

Three primary hypotheses were established before this research was conducted based on the findings of previous researchers. The first hypothesis was that Black Belt region residents experience higher rates of obesity compared to national averages. The participants involved in this research were found to have an overall overweight/obesity

rate of 41.9%, compared to a national average of 31.8%. Secondly, this research hypothesized that community physical environments, represented in this study as physical activity and food environments, contribute to the high risk of overweight and obesity in rural southern children. With respect to the physical activity environment, multilevel modeling found two variables—vegetative land cover and spatial video code to have significant correlations with higher percentiles of BMI, and three variables—walk score, urban land cover, and PA site density—to have significant correlations with lower percentiles of BMI. In terms of the food environment variables, multilevel modeling found three variables—convenience store, fast food restaurant, and full service restaurant—to be significantly associated with higher percentiles of BMI, and one variable—supermarkets/grocery stores—to be significantly associated with lower percentiles of BMI. The third and last hypothesis stated that community social environments can also contribute to increased risks of overweight and obesity in rural southern children. Multilevel modeling revealed significant associations among three variables—the school which the children attended, the percentage of African American population of the block group in which the children lived, and the age of the participant. With respect to school, participants which attended school farther away from urban clusters were found to have significantly increased percentiles of BMI. Participants from block groups with higher percentages of African American population also experienced increased percentiles of BMI. Lastly, as participants aged, percentile of BMI was found to significantly increase, with the highest rate of obesity being experienced among children 7 to 9 years old (44.6%).

5. Conclusions and Significance

5.1 Conclusions

This research serves to add to the existing literature concerning childhood obesity in relation to community physical environments, specifically physical activity and food environments. The goal was to target a previously understudied population (southern, low-income, rural, predominantly African American) in order to examine the complex interactions between socioeconomic disparities, community physical environments, and childhood obesity. This was accomplished through the assistance of GIS tools and techniques as well as statistical analysis using both quantitative and qualitative data. The findings from this research could serve to allow for better comprehension of how southern, rural, low-SES children can be affected by their surrounding environment.

Of the total sampled population, 41.9% were measured as overweight or obese, compared to a national average of 31.8%. All grouped obesity statistics (by gender, age, and school) also exceeded the national average. Results from individual demographic measures identified an alarmingly sharp spike of increased obesity and overweight rates from the age group of 4-6 to the age group of 7-9. This has important political implications that should highlight a need for intervention among children around this age group in order to counteract the increasing rates of obesity. This research also helps to highlight the detrimental effect that the study area (Black Belt) has on the population's

weight, and possibly provide intervention and mitigation strategies for rural, low-SES areas.

In the case of the PA environment, multilevel modeling highlighted the importance of particular types of land cover (urban) and of walkability in reducing obesity rates. For the food environment, particular types of food stores were highlighted and associated with their effect on obesity. Specifically, fast food restaurants, convenience stores, and full service restaurants were all found to have a significant effect in increasing obesity rates, while supermarkets were found to be associated with healthier weights. Community demographics also had significant effects on obesity rates, where higher percentages of African American population were associated with higher obesity rates. Schools were found to have a significant effect as well, with the rural schools having higher instances of obesity than the schools closer to urban areas.

The results of this research will add to the existing childhood obesity research literature while attempting to fill in gaps that have existed in this area of research in three primary ways. First, this research studied a very unique region. The underserved communities of Alabama's Black Belt region primarily consist of low-income, rural, minority individuals where serious health problems such as obesity are exaggerated. Identifying and reversing habits that lead to obesity will improve the health of children now and in the future.

Second, this research applied mixed methods in attempt to observe how physical environments affect obesity rates. The use of qualitative data in conjunction with the more commonly used quantitative data provided a more comprehensive view by which to assess obesity in relation to these environments. And different from most other research

topics that only include one aspect of the physical environment, this research identified two portions of the physical environment as potential factors for affecting obesity, the physical activity environment and the food environment.

Lastly, this research has political and social implications. Identification of factors promoting obesity in a rural minority community can lead to intervention of local leadership to promote healthier food options and more accessible PA sites. Ultimately this will lead to a healthier community helping to bridge the gap in socioeconomic and health disparities among rural populations.

This research identified a need for intervention among three specific groups children aged 7-9, children living in predominantly African American areas, and children attending school in rural areas. Increased rates of overweight and obesity were experienced in all three of these groups. Community leaders could benefit by working in conjunction with school officials, parks and recreation departments, department of transportation officials, grocers associations, and farmers associations in order to develop a community strategy which addresses issues related to insufficient access to healthy food and poor options for physical activity. A more in depth investigation might reveal that children in the 7-9 year age group were not participating in enough physical activity. In this instance, community leaders might work with the superintendent and principals of schools to implement increased amounts of physical activity to Physical Education (PE) classes, or to provide opportunities for more intensive physical activity. Additionally, a joint-use agreement between the city and local schools could also be arranged to provide access to school recreational facilities (ball fields, gymnasiums, etc.) for local community members after school hours. Or, perhaps the rural schools have issues with the

availability of healthy foods. Schools can work with local farmers or growers to acquire healthy foods that can be used for school meals, providing children with the opportunity to eat at least one healthy meal during the school day. Speaking in a more general manner, rural communities could benefit from the services of a professional similar to a city planner who could encourage the creation of healthier areas by implementing more opportunities for physical activity through venues such as parks, walking trails, or community centers, and by providing healthier food options through methods like community gardens or farmers markets.

5.2 Future Studies

This research had a few limitations that could be addressed in future studies. In regards to the PA environment, PA sites were identified without the input of local residents who would be more familiar with areas which are beneficial to the promotion of physical activity. They might also be able to provide additional PA sites which were either not listed or missed in data collection. No survey assessment of PA sites was distributed that could have allowed for participants to comment on aspects that weren't measured in this research such as safety of particular locations. In the future, a crime measurement could be implemented to judge the overall safety of block groups located within a study area. Limitations also exist for how the food environment was assessed. Huff's Model was used to illustrate the probabilities that children frequent particular food stores based only on two factors, travel distance and size of store. This ignores eating behaviors of participants and food choices within the food stores. No designation is made on the amounts or qualities of food that children consume from these locations. A questionnaire shining a light on eating behaviors could more accurately represent food

environments. Questionnaires could also serve to identify aspects which either draw in participants or keep them from frequenting certain locations, such as cleanliness of facilities, friendliness of staff, or selection of foods. This research also considers supermarkets to be beneficial and fast food restaurants to be detrimental to healthy weights. This does not take away from the fact that supermarkets still offer unhealthy items just as fast food restaurants offer healthy alternatives.

Future studies would benefit from the addition of measurements to assess the food and physical activity environments. In order to understand such a complex health issue as obesity in relation to physical environments, a more comprehensive measure of food and PA environments could be implemented through the addition of survey assessments of both the PA and food environments as well as eating behavior questionnaires. The addition of more qualitative variables could improve efforts to understand the intricate nature of community physical environments and their effects on obesity rates.

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Appendix A

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM) COURSEWORK REQUIREMENTS REPORT*

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

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IRB # 2 Social and Behavioral Emphasis - AU Personnel (Blue) - Basic/Refresher · Curriculum Group:

Course Learner Group: Same as Curriculum Group

 Stage:
 Description: Stage 1 - Basic Course
Choose this group to satisfy CITI training requirements for Investigators and staff involved primarily in Social/Behavioral Research with human subjects.

· Report ID: 12041728 • Completion Date: 01/12/2014 01/12/2017 Expiration Date: Minimum Passing: 80 · Reported Score*: 86

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
The Federal Regulations - SBE	01/09/14	4/5 (80%)
Assessing Risk - SBE	01/09/14	4/5 (80%)
Informed Consent - SBE	01/10/14	5/5 (100%)
Privacy and Confidentiality - SBE	01/12/14	4/5 (80%)
Students in Research	01/12/14	8/10 (80%)
Unanticipated Problems and Reporting Requirements in Social and Behavioral Research	01/12/14	3/3 (100%)
Belmont Report and CITI Course Introduction	01/12/14	3/3 (100%)
Research with Children - SBE	01/12/14	4/4 (100%)
Research in Public Elementary and Secondary Schools - SBE	01/12/14	3/4 (75%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid independent Learner.

CITI Program

Emall: citisupport@miami.edu
Phone: 305-243-7970
Web: https://www.citiprogram.org

** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

William Carter (ID: 3926555) · Name: • Email: wmc0005@auburn.edu • Institution Affiliation: Auburn University (ID: 964) Institution Unit: Geology and Geography

· Phone: 256-206-2268

Curriculum Group: IRB # 2 Social and Behavioral Emphasis - AU Personnel (Blue) - Basic/Refresher

 Course Learner Group: Same as Curriculum Group · Stage: Stage 1 - Basic Course

Choose this group to satisfy CITI training requirements for Investigators and staff involved primarily in Social/Behavioral Research with human subjects. · Description:

· Report ID: 12041728 · Report Date: 02/18/2015 · Current Score**: 89

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
Students in Research	01/12/14	8/10 (80%)
Belmont Report and CITI Course Introduction	01/12/14	3/3 (100%)
The Federal Regulations - SBE	01/09/14	4/5 (80%)
Assessing Risk - SBE	01/09/14	4/5 (80%)
Informed Consent - SBE	01/10/14	5/5 (100%)
Privacy and Confidentiality - SBE	01/12/14	4/5 (80%)
Research with Children - SBE	01/12/14	4/4 (100%)
Research in Public Elementary and Secondary Schools - SBE	02/16/14	4/4 (100%)
Unanticipated Problems and Reporting Requirements in Social and Behavioral Research	01/12/14	3/3 (100%)

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CITI Program

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William Carter (ID: 3926555) · Name: wmc0005@auburn.edu • Email: • Institution Affiliation: Aubum University (ID: 964) Geology and Geography

• Institution Unit: • Phone: 256-206-2268

· Curriculum Group: Social and Behavioral Responsible Conduct of Research

Course Learner Group: Social, Behavioral and Education Sciences

Stage 1 - RCR · Stage:

This course is for investigators, staff and students with an interest or focus in **Social and Behavioral** research. This course contains text, embedded case studies AND quizzes. · Description:

· Report ID: 12041699 Completion Date: 01/13/2014 Expiration Date: N/A Minimum Passing: · Reported Score*: 85

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
Introduction to the Responsible Conduct of Research Archived 1248	01/13/14	No Quiz
Research Misconduct (RCR-SBE)	01/13/14	4/5 (80%)
Data Management (RCR-SBE)	01/13/14	4/5 (80%)
Authorship (RCR-SBE)	01/13/14	5/5 (100%)
Peer Review (RCR-SBE)	01/13/14	4/5 (80%)
Mentoring (RCR-Interdisciplinary)	01/13/14	4/5 (80%)
Using Animal Subjects in Research (RCR-Basic)	01/13/14	5/5 (100%)
Conflicts of Interest (RCR-SBE)	01/13/14	5/6 (83%)
Collaborative Research (RCR-SBE)	01/13/14	4/5 (80%)
Research Involving Human Subjects (RCR-Basic)	01/13/14	4/5 (80%)
Responsible Conduct of Research (RCR) Course Conclusion	01/13/14	No Quiz

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid independent Learner.

** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

• Name: William Carter (ID: 3926555) wmc0005@auburn.edu · Email: • Institution Affiliation: Auburn University (ID: 964) Geology and Geography 256-206-2268 • Institution Unit: · Phone:

 Curriculum Group: Social and Behavioral Responsible Conduct of Research

Course Learner Group: Social, Behavioral and Education Sciences

· Stage: Stage 1 - RCR

This course is for investigators, staff and students with an interest or focus in **Social and Behavioral** research. This course contains text, embedded case studies AND quizzes. Description:

· Report ID: 12041699 • Report Date: 02/18/2015 · Current Score**: 85

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
Mentoring (RCR-Interdisciplinary)	01/13/14	4/5 (80%)
Using Animal Subjects in Research (RCR-Basic)	01/13/14	5/5 (100%)
Research Involving Human Subjects (RCR-Basic)	01/13/14	4/5 (80%)
Introduction to the Responsible Conduct of Research Archived 1248	01/13/14	No Quiz
Conflicts of Interest (RCR-SBE)	01/13/14	5/6 (83%)
Collaborative Research (RCR-SBE)	01/13/14	4/5 (80%)
Research Misconduct (RCR-SBE)	01/13/14	4/5 (80%)
Authorship (RCR-SBE)	01/13/14	5/5 (100%)
Peer Review (RCR-SBE)	01/13/14	4/5 (80%)
Data Management (RCR-SBE)	01/13/14	4/5 (80%)
Responsible Conduct of Research (RCR) Course Conclusion	01/13/14	No Quiz

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

CITI Program
Email: ditsupport@miami.edu
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* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

Name: William Carter (ID: 3926555)
 Email: wmc0005@auburn.edu
 Institution Affiliation: Auburn University (ID: 964)
 Institution Unit: Geology and Geography

• Phone: 256-206-2268

Curriculum Group: Course In The Protection Human Subjects

• Course Learner Group: Research with Children - SBR
• Stage: Stage 1 - Basic Course

• Report ID: 12041695
• Completion Date: 01/12/2014
• Expiration Date: 01/12/2017
• Minimum Passing: 80
• Reported Score*: 100

 REQUIRED AND ELECTIVE MODULES ONLY
 DATE COMPLETED
 SCORE

 Research with Children - SBE
 01/12/14
 4/4 (100%)

 Auburn University
 01/12/14
 No Quiz

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

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• Name: William Carter (ID: 3926555) Email: wmc0005@auburn.edu
 Institution Affiliation: Auburn University (ID: 964) Geology and Geography 256-206-2268 Institution Unit: • Phone:

Curriculum Group: Course In The Protection Human Subjects

· Course Learner Group: Research with Children - SBR

· Stage: Stage 1 - Basic Course

12041695 Report ID: 02/18/2015 Report Date: · Current Score**: 100

MOST RECENT SCORE REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES 4/4 (100%) Research with Children - SBE 01/12/14 01/12/14 No Quiz Auburn University

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CITI Program

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

William Carter (ID: 3926555) · Name: wmc0005@auburn.edu • Email: • Institution Affiliation: Auburn University (ID: 964) Geology and Geography · Institution Unit: · Phone: 256-206-2268

· Curriculum Group: Course In The Protection Human Subjects

Course Learner Group: Research in Public Elementary and Secondary Schools - SBR

Stage 1 - Basic Course Stage:

 Report ID:
 Completion Date: 12369476 02/16/2014 • Expiration Date: 02/16/2017 Minimum Passing: · Reported Score*: 100

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
Research in Public Elementary and Secondary Schools - SBE	02/16/14	4/4 (100%)
Auburn University	01/12/14	No Quiz

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

CITI Program
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Web: https://www.citiprogram.org

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** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

• Name: William Carter (ID: 3926555) • Email: wmc0005@auburn.edu • Institution Affiliation: Auburn University (ID: 964) Geology and Geography 256-206-2268 Institution Unit: · Phone:

Curriculum Group: Course In The Protection Human Subjects

Course Learner Group: Research in Public Elementary and Secondary Schools - SBR

· Stage: Stage 1 - Basic Course

12369476 • Report ID: 02/18/2015 Report Date: · Current Score**: 100

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
Research in Public Elementary and Secondary Schools - SBE	02/16/14	4/4 (100%)
Auburn University	01/12/14	No Quiz

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

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* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

William Carter (ID: 3926555) • Name: wmc0005@auburn.edu · Email: • Institution Affiliation: Auburn University (ID: 964) Geology and Geography · Institution Unit: 256-206-2268 · Phone:

Curriculum Group: Course In The Protection Human Subjects
 Course Learner Group: Research with Protected Populations - Vulnerable Subjects: An Overview

Stage 1 - Basic Course Stage:

12369475 · Report ID: Completion Date:
 Expiration Date: 02/16/2014 02/16/2017 Minimum Passing: · Reported Score*:

DATE COMPLETED SCORE REQUIRED AND ELECTIVE MODULES ONLY 4/4 (100%) Research With Protected Populations - Vulnerable Subjects: An Overview 02/16/14 No Quiz 01/12/14 Auburn University

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

CITI Program

** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

· Name: William Carter (ID: 3926555) wmc0005@auburn.edu • Email: • Institution Affiliation: Auburn University (ID: 964) Geology and Geography 256-206-2268 • Institution Unit:

· Phone:

Curriculum Group: Course In The Protection Human Subjects

Course Learner Group: Research with Protected Populations - Vulnerable Subjects: An Overview

· Stage: Stage 1 - Basic Course

12369475 Report ID: 02/18/2015 • Report Date: · Current Score**: 100

MOST RECENT SCORE REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES 4/4 (100%) 02/16/14 Research With Protected Populations - Vulnerable Subjects: An Overview 01/12/14 No Quiz Auburn University

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

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Appendix B



COLLEGE OF SCIENCES AND MATHEMATICS DEPARTMENT OF GEOLOGY AND GEOGRAPHY

(Note: DO NOT AGREE TO PARTICIPATE UNLESS AN IRB APPROVAL STAMP WITH CURRENT DATA HAS BEEN APPLIED TO THIS DOCUMENT.)

PARENTAL PERMISSION/CHILD ASSENT for a Research Study Entitled

"Socioeconomic Disparities and Childhood Obesity in Alabama's Black Belt Region"

Your child is invited to participate in a research study to examine the association between built and social environments, individual psychological stress, as well as children's eating behavior, physical activity and weight status. The study is being conducted by Dr. Yingru Li (Assistant Professor), master student (Mitch Carter), and undergraduate student (Austin Bush) of the Department of Geology and Geography, as well as Dr. Leah Robinson (Associate Professor) of the School of Kinesiology at Auburn University. Your child was selected as a possible participant because she or he is a primary school student at age of 10-12. Since your child is age 18 or younger we must have your permission to include him/her in the study.

If you decide to allow your child to participate in this research study, your child will be asked to complete a questionnaire concerning her/his weight status, eating behavior, physical activity, psychological stress, and home environment. Your home address and such demographic information as gender, race, and parents' education levels will be also asked during the survey for data analysis. If you or your child feels uncomfortable to tell us the home address, your child can list two streets closest to your home and we will use the intersection of these two streets in data analysis. Your child's total time commitment will be approximately 1 hour.

If your child participates in this study, your child can expect to learn more knowledge of the factors that influence their weight status and health outcomes. Also we will report the measured weight, height, and BMI (anonymous) to the school nurses, which will provide the school health professionals valuable knowledge and data about children's health. We cannot promise you that your child will receive any or all of the benefits described.

If you (or your child) change mind about your child's participation, your child can be withdrawn from the study at any time. Your child's participation is completely voluntary. If you choose to withdraw your child, your child's data can be withdrawn as long as it is identifiable. Your decision about whether or not to allow your child to participate or to stop participating will not jeopardize your or your child's future relations with Auburn University, the Department of Geology and Geography and the School of Kinesiology.

Your child's privacy will be protected. Any information obtained in connection with this study will remain anonymous or confidential. The data collected will be put in a locked room. Information obtained through your child's participation may be used to in a master's thesis, published in professional journals, and presented at professional meetings. Any information that identifies your child will not be revealed in the items listed above.

If you (or your child) have questions about this study, please ask the interviewers now or contact Dr. Yingru Li at 334-844-4069 or Dr. Leah Robinson at 334-844-8055. A copy of this document will be given to you to keep.

Participant's initials_____

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Protection University in the supproved the Solid Institutional Review Court in the Solid Institution of 13/13/15

Protection 14/07 2 EP 14/03

GEOLOGY & GEOGRAPHY

210 PETRIE HALL

AUBURN, AL 36849-5418

PHONE: 334-844-4282

FAX: 33-844-4486

www.auburn.edu

If you have questions about your child's rights as a research participant, you may contact the Auburn University Office of Human Subjects Research or the Institutional Review Board by phone (334)-844-5966 or e-mail at hsubjec@auburn.edu or IRBChair@auburn.edu.

HAVING READ THE INFORMATION PROVIDED, YOU MUST DECIDE WHETHER OR NOT YOU WISH FOR YOUR CHILD TO PARTICIPATE IN THIS RESEARCH STUDY. YOUR SIGNATURE INDICATES YOUR WILLINGNESS TO ALLOW YOUR CHILD TO PARTICIPATE.

Participant's signature Date Investigator obtaining consent Date

Printed Name Printed Name

Parent/Guardian Signature Date

Printed Name

Protocol # 12-072 B 14-03

Page 2 of 2