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The relationship between obesity and socioeconomic status among Texas school children and its spatial variation

He Jin*, Yongmei Lu

Department of Geography, Texas State University, 601 University Dr., San Marcos, TX, 78666, United States

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ABSTRACT

Understanding the relationships between obesity and socioeconomic status (SES) among school children and the spatial variation of such relationship is essential for developing appropriate intervention strategies. In this study, we employed Local Entropy Map (LEM) to explore the spatial patterns of the relationship at school district level in Texas. Children's obesity was measured by Body Mass Index (BMI). The BMI data for this study were obtained from Physical Fitness Assessment Initiative (PFAI) program that has been coordinated by Texas Education Agency (TEA). SES was described by six variables, which were further reduced into two factors, namely Household SES and Neighborhood SES. The study period was 2012–2013 academic year. LEM analyses revealed clear spatial variation of the relationship between obesity and SES at school-district level. In particular, the prevalence of obesity among school children was found to be significantly related to Household SES and Neighborhood SES in four regions in Texas. These four regions are centered in major metropolitan areas in Texas, including San Antonio, Dallas-Fort Worth, Houston, and Lubbock. Further regression analyses showed variation of the relationship across these four regions. Obesity among school children in Texas was found to be more related to Household SES than Neighborhood SES; the relationship was strongest in San Antonio region. These findings may suggest the presence of obesogenic environment in the low SES school districts in these regions. Further studies to examine the particular nature of the obesogenic environment in these school districts are needed in order to support the development of regionalized policy and practice that can be more effective in addressing locale specifics.

1. Introduction

Childhood overweight and obesity has become a big concern for public health in both developed and developing countries (Hoelscher et al., 2004; Ji, 2005; Kim, Ahn, & Nam, 2005; Rennie & Jebb, 2005; Wang, Monteiro, & Popkin, 2002; Williams, Wake, Hesketh, Maher, & Waters, 2005). The prevalence of childhood obesity among children 6–11 years old in the United States has increased from 6.5% in 1976 to 18.8% in 2004 (Franzini et al., 2009). In 2002, 20% of Texas children were considered either overweight or obese, higher than the national average (Pérez et al., 2011). Obesity is known to contribute to a number of health risks, including cardiovascular disease, diabetes, and mental illness (Anderson, Cohen, Naumova, Jacques, & Must, 2007; Freedman, Mei, Srinivasan, Berenson, & Dietz, 2007; Low, Chin, & Deurenberg-Yap, 2009; Minck, Ruiter, Van Mechelen, Kemper, & Twisk, 2000). Moreover, obesity in childhood is likely to persist into adolescence and adulthood, causing various chronic health problems and resulting in lifetime negative consequences (Dietz, 1998; Singh, Mulder, Twisk, Van Mechelen, & Chinapaw, 2008). Therefore, understanding the factors contributing to the epidemic of obesity and developing proper intervention strategies to reduce childhood obesity is essential for the health of school children (Penney, Rainham, Dummer, & Kirk, 2014).

Epidemiologists have long tried to determine factors influencing childhood overweight and obesity. Traditional studies focused on food intake, physical activity, biology, and individual behaviors, but they tended to overlook the influences of *environment* (Egger & Swinburn, 1997). Understanding *environment* components including physical conditions, culture, and SES, are important for battling obesity as these factors also contribute to the development of overweight and obesity. Egger and Swinburn (1997) suggested that obesity intervention should shift from traditional treatment to accounting for environmental or ecological factors. Swinburn,

* Corresponding author.
E-mail addresses: h_j29@txstate.edu (H. Jin), YL10@txstate.edu (Y. Lu).

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Egger, and Raza (1999) developed the concept of *obesogenic environment* to describe a series of factors such as built environment, culture, SES, and politics; these factors, through interacting with individual behavior, may help produce and sustain obesity and overweight problem. Assessing factors that may contribute to *obesogenic environment,* such as SES, may provide insights for effective intervention of childhood overweight and obesity, as suggested by recent studies (Cecil et al., 2005; Lake & Townshend, 2006; Wardle, Carnell, Haworth, & Plomin, 2008). In Texas, more students are at a SES disadvantaged situation than the national average. In the 2012–2013 school year, a total of 3,109,460 Texas students were identified as being economically disadvantaged, accounting for 60.26% of the students in the state.[1] Investigating the relationship between SES and obesity prevalence for Texas students may provide significant insights for intervention strategies to manage the epidemic.

The measure of SES involves three different levels: individual level, family or household level, and neighborhood level (Krieger, Williams, & Moss, 1997); each level represents different facets of SES. Individual SES focuses on the measure of education, occupation, and income of a single individual. Household SES defines a basic unit for an individual to live in a society and can be reflected by measures such as household income and household savings. Neighborhood SES describes a broader context and measures the SES for a group of people who live in a neighborhood. Examples of indicators for neighborhood SES may include the percentage of people who are Hispanic/Latino and the percentage of people renting house in a neighborhood. These indicators reflect the overall condition of a neighborhood.

Previous studies have examined the effects of different levels of SES on the health outcomes of population (Gould & Jones, 1996; Malmström, Johansson, & Sundquist, 2001; Pickett & Pearl, 2001; Robert, 1998). These studies highlighted the importance of investigating different levels of SES since the association between SES factors and adolescent obesity may differ at different scales. However, most of the existing studies on the relationship between SES and childhood obesity took a spatially stationary approach, meaning that they did not effectively treat the spatial aspects of obesity nor SES, let alone the spatial variation of their relationship. These studies assumed a constant relationship between SES and obesity prevalence across a study area. But, the reality is that the relationship between obesity and the factors defining *obesogenic environment* vary over geographic space (Swinburn et al., 1999). It is important to examine the spatial variation of the relationship and to identify its significant local patterns.

Geographically Weighted Regression (GWR) is commonly used to reveal the spatial variation of a relationship between a dependent variable and one or more independent variables (Chang, Lin, & Su, 2008; Moore & Myers, 2010; Park, 2004; Partridge, Rickman, Ali, & Olfert, 2008). GWR has been used to explore the relationship between obesity and different independent variables such as parcel-level economic disadvantages and food environment (Chen & Truong, 2012; Chi, Grigsby-Toussaint, Bradford, & Choi, 2013). However, as Guo (2010) argued, GWR can only capture linear relationship. In other words, GWR is limited for exploring the possible non-linear nature of the relationship between obesity and obesogenic environmental factors. Moreover, the variable transformation that is conducted when running GWR may result in a variety of issues, including multicollinearity among independent variables, model misspecification, and spatial autocorrelation in residuals (Guo, 2010).

To overcome the limitations of GWR, Guo (2010) proposed the *Local Entropy Map (LEM)* method, a nonparametric approach to detect significant multivariate relationship at local scale. Guo's *LEM* method calculates an approximate Renyi entropy for the multivariate data of each local neighborhood, and then estimates *p*-value for the entropy of each local region using permutation methods and based on different statistical tests. The final output of *LEM* is a map of *p*-values of local entropy across the study area. A small *p*-value indicates high confidence and low uncertainty about a possibly strong relationship between the dependent variable and the independent variable(s) at a local neighborhood. Further investigation can follow to examine the form and magnitude of the relationship at a particular neighborhood. Compared to GWR, *LEM* can detect local multiple relationship, including linear, nonlinear and other forms of relationship. Moreover, *LEM* is robust in handling noise and outliers. For the technical details of *LEM*, one can refer to Guo (2010).

This study employed *LEM* to investigate the spatial variation of the relationship between the prevalence of obesity and SES among school children across the State of Texas. The study sought to answer the following questions: (1) which region(s) in Texas shows a significant relationship between the prevalence of obesity among school children and SES at school district level? (2) What are the nature and magnitude of the relationship at each region, and how does the relationship vary across regions? Two major steps were taken to seek answers to these questions. First, we used *LEM* to identify contiguous regions in Texas where the prevalence of obesity in school children has a significant relationship with SES. Second, we employed data exploration and regression techniques to examine and identify the specific relationship at these particular regions. Understanding the spatial patterns of this relationship can help policy makers develop effective public health promotion policies at the regional level (Procter, Clarke, Ransley, & Cade, 2008). Knowing the spatial variation of such relationship in Texas is critical for developing regional and local policies and intervention strategies to tackle the epidemic of obesity.

2. Material and method

2.1. Data preparation

The children's obesity data in 2012–2013 were extracted from the Physical Fitness Assessment Initiative (PFAI) dataset that is collected and distributed by Texas Education Agency (TEA) (Texas Education Agency, 2014). Under PFAI, all public schools in Texas are required to perform annual physical fitness evaluation for student samples in grades 3–12. In addition to height and weight data, individual physical fitness data are collected through five fitness tests. Body Mass Index (BMI), defined as the ratio of weight in kilograms to the square of height in meters, was derived and reported for each student. While BMI is not a direct measure of body fatness (Index, 2008; The Cooper Institute, 2014), a high BMI indicates a high risk for overweight and obesity for most people, and is therefore commonly used to decide if one is overweight or obese.[2] For the purpose of evaluating students' health status, PFAI program classified student's BMI level into three zones by considering sex and age (The Cooper Institute, 2014), namely *Healthy Fitness Zone* (indicating sufficient fitness for good health), *Needs Improvement – Some Risk Zone* (meaning presence of certain level of risk), and *Needs Improvement – High Risk Zone* (meaning high risk and unhealthy). For this research, the prevalence of obesity in school children was measured as the percentage of students in a school

[1] See https://rptsvr1.tea.texas.gov/adhocrpt/adstc.html.

[2] See http://www.nhlbi.nih.gov/health/health-topics/topics/obe/diagnosis for more information.