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Spatial clustering patterns of child weight status in a southeastern US county

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A B S T R A C T

Youth obesity is a major public health concern due to associated physical, social, and psychological health consequences. While rates and disparities of youth obesity levels are known, less research has explored spatial clustering patterns, associated correlates of spatial clustering, comparing patterns in urban and rural areas. Therefore, this study 1) examined spatial clustering of youth weight status, 2) investigated sociodemographic correlates of spatial clustering patterns, and 3) explored spatial patterns by level of urbanization. This study occurred in a southeastern US county (pop:474,266) in 2013. Trained physical education teachers collected height and weight for all 3rd-5th grade youth ($n = 13,469$) and schools provided youth demographic attributes. BMI z-scores were calculated using standard procedures. Global Moran's Index and Anselin's Local Moran's I (LISA) were used detect global and local spatial clustering, respectively. To examine correlates of spatial clustering, BMI z-score residuals from a series of four linear regression models were spatially analyzed, mapped, and compared. SAS 9.4 and GeoDA were used for analyses; ArcGIS was used for mapping. Significant, positive global clustering (Index = 0.04,$p < 0.001$) was detected. LISA results showed that about 4.7% ($n = 635$) and 7.9% ($n = 1058$) of the sample were identified as high and low obesity localized spatial clusters ($p < 0.01$), respectively. Individual and neighborhood sociodemographic characteristics accounted for the majority of spatial clustering and differential patterns were observed by level of urbanization. Identifying geographic areas that contain significant spatial clusters is a powerful tool for understanding the location of and exploring contributing factors to youth obesity.

1. Introduction

Childhood obesity has been recognized as a major public health problem of the 21st century due to the wide array of physical, social, and emotional health consequences that often accompany overweight and obesity in youth (Ogden, Carroll, Kit, & Flegal, 2014; Reilly et al., 2003; Strong et al., 2005). Studies have also documented that overweight and obese youth have a higher risk for increased weight status into adolescence and adulthood (Cunningham, Kramer, & Narayan, 2014; Wang & Beydoun, 2007). and persistent adult obesity is related to decreased quality of life, increased rates of chronic disease and healthcare costs, as well as increased morbidity and mortality (Sallis, Floyd, Rodríguez, & Saelens, 2012; Wang, McPherson, Marsh, Gortmaker, & Brown, 2011). Disparities in childhood obesity rates also exist in most developed countries; in the U.S. youth who are low-income, racial/ethnic minorities, and live in the southeastern U.S. have higher rates of overweight and obesity (Singh et al., 2007, 2008).

Researchers and practitioners have recognized complex causes of youth obesity, with many individual, interpersonal, community, environmental, and societal factors contributing to weight status (Han, Lawlor, & Kimm, 2010; Pereira, Nogueira, & Padez, 2018; Xu, Wen, & Wang, 2015). As a result, multidisciplinary theoretical models are frequently employed frameworks to understand the childhood obesity determinants and patterns at a population level (McLeroy, Bibeau, Steckler, & Glanz, 1988; Pereira et al., 2018; Sallis et al., 2006, 2012; Story, Kaphingst, Robinson-O'Brien, & Glanz, 2008; Xu et al., 2015).

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Integrating advanced spatial analytical tools and analyses with childhood obesity research is one example of applying a multidisciplinary approach to a widespread public health problem in order to advance this area of research.

Spatial variables and analyses are essential elements when exploring geographic patterns of health outcomes, which relies on computer-based geographic information systems (GIS) software and technology to visualize, measure, and conduct analyses (Auchincloss, Gebreab, Mair, & Roux, 2012; Casey et al., 2014; Jerrett, Gale, & Kontgis, 2010). Although broad public health literature has seen an increase in the use of GIS applications, obesity-related research could benefit from continued application of spatial tools and analyses when examining patterns and determinants (Auchincloss et al., 2012). Many studies documenting the prevalence of obesity distribution by geographic areas have aggregated data at administratively-defined units (e.g., census tracts, ZIP codes, cities, states) to analyze and describe the prevalence or rates of overweight or obesity (Auchincloss et al., 2012; Ford, Mokdad, Giles, Galuska, & Serdula, 2005; Koh, Grady, & Vojnovic, 2015; Singh et al., 2007, 2010; Wang & Beydoun, 2007); these methodologies have served as a critical foundation for understanding obesity rates locally, nationally, and internationally. Utilizing global and local spatial clustering analyses to explore localized patterns that are not necessarily constrained by administrative units can offer unique insight into individual-level geographic obesity patterns (Huang, Moudon, Cook, & Drewnowski, 2015; Laraia et al., 2014; Penney, Rainham, Dummer, & Kirk, 2014; Pouliou & Elliott, 2009).

To date, two of the primary spatial tools that have been most used in public health research are spatial proximity (i.e., measuring the distance between two points) and spatial aggregation methods. Spatial clustering is a useful spatial analysis that can conceptually, technically, and practically advance obesity research. First, spatial clustering analyses offers a tool to measure the nature and strength of geographical interdependence between data, which can conceptually show researchers where patterns of health outcomes may or may not be closely related (Auchincloss et al., 2012; Penney et al., 2014; Rushton, 2003). Indeed, other researchers have applied spatial clustering tools and analyses to understanding distributions of important public health problems, such as human anthrax (Barro et al., 2015) and cancer (Lin et al., 2015), yet obesity remains less explored with these powerful tools. The second reason to conduct these analyses is if significant spatial autocorrelation is present, the statistical assumption of independent observations for many additional statistical analyses may be violated (Rezaeian, Dunn, Leger, & Appleby, 2007). Consequently, assessing spatial autocorrelation is recommended as a first step in place-focused obesity research to minimize overstating significance between exposures and outcomes; this study demonstrates how this methodology can be applied in research (Rezaeian et al., 2007). Third, mapping patterns that are identified with clustering analyses can result in powerful visualizations, which may be used to pinpoint communities uniquely impacted by chronic disease outcomes, like obesity (Huang et al., 2015; Penney et al., 2014). These types of maps, combined with maps showing obesity prevalence statistics could be particularly impactful for practitioners in highlighting priority areas for intervention. Last, exploring social and economic determinants of particular spatial clustering patterns, not only the obesity outcome itself, is a critical step towards understanding how geographic patterns emerge.

To date, some studies have employed spatial clustering analyses to examine unique geographic patterns of obesity; however, there are some advancements that warrant further attention in this area of literature (Fritz, Schuurman, Robertson, & Lear, 2013). First, among studies that have examined obesity clustering, the vast majority have focused on adults (Curtis & Lee, 2010; Gartner, Taber, Hirsch, & Robinson, 2016; Huang et al., 2015; Laraia et al., 2014; Mobley, Finkelstein, Khavjou, & Will, 2004; Pouliou & Elliott, 2009; Schuurman, Peters, & Oliver, 2009); to our knowledge, only a few studies have investigated spatial clustering of child or adolescent obesity (Hernández-Vásquez et al., 2016; Jin & Lu, 2017; Penney et al., 2014). Second, many studies that have explored spatial clustering of obesity conducted analyses with large-scale administrative units, such as census tracts, zip codes, or states (Curtis & Lee, 2010; Gartner et al., 2016; Hernández-Vásquez et al., 2016; Mobley et al., 2004; Pouliou & Elliott, 2009; Schuurman et al., 2009). Conducting spatial clustering analyses at an individual level (i.e., point data) may provide added information on smaller scale, or localized, patterns in the study area that would not be identified (Huang et al., 2015; Laraia et al., 2014). Finally, some studies have also examined whether demographic (e.g., socioeconomic status) and community-level factors (e.g., physical activity and nutrition environments) are related to the geographic patterning of obesity. Among those studies, economic indicators have emerged as some of the main explanatory variables of observed spatial patterns (Chalkias et al., 2013; Huang et al., 2015; Jin & Lu, 2017; Laraia et al., 2014). For example, Chalkias and colleagues found that education level was the most significant predictor of childhood obesity in Greece (Chalkias et al., 2013), whereas Chen and Troung found that socioeconomic disadvantage was only significantly related to obesity in specific geographic townships in Taiwan (Chen & Truong, 2012). Examining how identified spatial clusters change as economic and other demographic variables are included in spatial analytical models is essential to better understand location-specific patterns of childhood obesity.

In addition to these aforementioned gaps, few studies have explored patterns of obesity by varying levels of urbanization. Indeed, in large metropolitan areas may only contain urban areas and not warrant more nuanced analyses. However, many cities across the globe contain substantial diversity in levels of urbanization within the boundaries, including suburban and rural areas proximal to urban city centers. The contextual differences between urban, suburban, and rural may substantially influence youth health behaviors and weight status, and subsequently, result in varying types and degrees of spatial clustering of youth obesity (Hennessy et al., 2010; Liu et al., 2008, 2012). Furthermore, rural areas have been acknowledged as another focus of youth obesity disparities in the U.S. because children in these areas demonstrate higher rates of overweight and obesity (Lutfiyya, Lipsky, Wisdom-Behounek, & Inpanbutr-Martinkus, 2007). More spatially specific analyses are needed to compare patterns by urban, suburban, and rural areas.

To address these gaps in the literature and apply infrequently used spatial analyses to advance childhood obesity research, the objectives of this study were to 1) analyze spatial clustering patterns of childhood obesity in a southeastern US County, 2) examine whether socio-demographic characteristics were associated with spatial clustering patterns of youth obesity, and 3) explore differential spatial clustering patterns of obesity by levels of urbanization.

2. Methods

2.1. Study setting

This study occurred in 2013 in a large county in the southeastern United States, which had a total population of 474,266, of which 77.1% was Non-Hispanic White, 18.5% was African American, and 8.5% was Hispanic or Latino (United States Census Bureau, 2013a). In 2013, the median household income of the county was $48,886 and approximately 15.0% of residents lived below the federal poverty line (United States Census Bureau, 2013a). The county encompassed approximately 750 square miles of land area.

2.2. Measures and data collection

2.2.1. Youth obesity and demographic characteristics

As part of regular protocol, trained physical education teachers measured and recorded the height and weight for all children in 3rd through 5th grade (n = 14,232) enrolled in all 51 public elementary