Regional Disparities in Obesity Prevalence in the United States: A Spatial Regime Analysis

Candice A. Myers1, Tim Slack2, Corby K. Martin1, Stephanie T. Broyles1, and Steven B. Heymsfield1

Objective: Significant clusters of high- and low-obesity counties have been demonstrated across the United States (US). This study examined regional disparities in obesity prevalence and differences in the related structural characteristics across regions of the US.

Methods: Drawing on model-based estimates from the Centers for Disease Control and Prevention, regional differences in county-level adult obesity prevalence (percent of the adult population [≥ 20 years] that was obese [BMI ≥ 30 kg/m²] within a county, 2009) were assessed with a LISA (Local Indicators of Spatial Association) analysis to identify geographic concentrations of high and low obesity levels. Regional regime analysis was utilized to identify factors that were differentially associated with obesity prevalence between regions of the US.

Results: High- and low-obesity county clusters and the effect of a number of county-level characteristics on obesity prevalence differed significantly by region. These included the positive effect of African American populations in the South, the negative effect of Hispanic populations in the Northeast, and the positive effect of unemployed workers in the Midwest and West.

Conclusions: Our findings suggest the need for public health policies and interventions that account for different regional characteristics underlying obesity prevalence variation across the US.

Introduction

Public health research has shown that the prevalence of obesity and related chronic diseases is not evenly distributed across the United States (US), but instead tend to be geographically patterned (1-5). Results from one recent study suggested that the South was particularly notable for clusters of high-obesity counties, while other regions, such as the West and Northeast, demonstrated clusters of low-obesity counties, and that local social, economic, and environmental correlates of obesity prevalence also differed across geographic space (6). Given this evidence, further research was warranted to investigate regional differences in obesity prevalence across the US and identify county-level attributes that underlie existing regional differences. Results will provide evidence of the need to geographically tailor public health policies and interventions to address issues unique to regional areas in order to achieve efficacious health improvement.

This study focused on differences in county-level adult obesity prevalence across the four Census Bureau-defined regions of the US: South, Northeast, West, and Midwest (7). We used the Centers for Disease Control and Prevention’s (CDC) Diabetes Interactive Atlas, which provides model-based estimates of adult obesity prevalence for 2009 among US counties (8). These data allowed us to address the hypotheses of this study, which were that 1) spatial differences exist in county-level adult obesity prevalence across regions of the US and 2) associations between county-level adult obesity prevalence and county features differ between the regions of the US. This objective advances purely descriptive approaches by examining significant geographic variation in obesity prevalence (4) and builds upon research demonstrating significant spatial patterns of obesity prevalence across US counties (6). Accordingly, this study holds implications for community-based obesity treatment and prevention efforts that apply a universal or one-size-fits-all approach to addressing the obesity epidemic.

Methods

Data sources and variables

The present analysis used counties and county equivalents, including parishes in Louisiana and independent cities in Virginia, as the units of analysis. The Regional Disparities in Obesity Prevalence in the United States: A Spatial Regime Analysis study used model-based estimates from the Centers for Disease Control and Prevention’s (CDC) Diabetes Interactive Atlas, which provides model-based estimates of adult obesity prevalence for 2009 among US counties (8). These data allowed us to address the hypotheses of this study, which were that 1) spatial differences exist in county-level adult obesity prevalence across regions of the US and 2) associations between county-level adult obesity prevalence and county features differ between the regions of the US. This objective advances purely descriptive approaches by examining significant geographic variation in obesity prevalence (4) and builds upon research demonstrating significant spatial patterns of obesity prevalence across US counties (6). Accordingly, this study holds implications for community-based obesity treatment and prevention efforts that apply a universal or one-size-fits-all approach to addressing the obesity epidemic.

Acknowledgments

This study was supported by the National Heart, Lung, and Blood Institute (NHLBI) grant 1R01HL121066 and the National Institute of Child Health and Human Development (NICHD) grant 2R01HD058273. The authors declare no conflict of interest.

Author contributions: Myers had full access to all of the data in the study and takes responsibility for the accuracy of the analysis. Study concept and design: Myers, Slack, Martin, Broyles, Heymsfield. Acquisition of data: Myers. Analysis and interpretation of data: Myers. Drafting the manuscript: Myers, Slack, Martin, Broyles, Heymsfield. Critical revision of the manuscript for important intellectual content: Myers, Slack, Martin, Broyles, Heymsfield.

Additional Supporting Information may be found in the online version of this article.

Received: 17 June 2014; Accepted: 16 October 2014; Published online 17 December 2014. doi:10.1002/oby.20963
Regional Disparities in Adult Obesity

Myers et al.

of analysis (excluding Alaska and Hawaii). We relied upon county-level obesity estimates from the CDC as the dependent variable, specifically, the percent of the adult population (≥20 years) that was obese (BMI ≥ 30 kg/m²) within a county for 2009 (8). County-level estimates of diabetes and selected risk factors (e.g., obesity, leisure-time physical inactivity) are model-based and derived from data using the CDC’s Behavioral Risk Factor Surveillance System (BRFSS) (9) and the US Census Bureau’s Population Estimates Program (10). While the BRFSS currently samples from nearly every county in the nation, small sample sizes prevent the direct calculation of reliable county-specific estimates for most US counties. To overcome this limitation, the CDC has drawn on the aforementioned data to develop county-level obesity prevalence estimates for all US counties using model-based small area estimation techniques. To increase the precision of year-specific county-level estimates, 3 years of BRFSS data are pooled for a given time point. For example, the CDC estimates for 2009 were based on data from 2008, 2009, and 2010, totaling approximately 1.3 million respondents. Validation-studies have compared estimates produced by this modeling technique against direct estimates from counties with large enough sample sizes and have shown little disagreement between the direct and model-based estimates (11). Those involved in the production of the CDC’s diabetes and associated risk factors estimates have encouraged research that explicitly incorporates spatial effects to describe and account for county-level patterns in these data (1,5).

Drawing from Hillemeier et al., who theorized pathways through which community features impact health (12), conceptually relevant independent variables that tapped into multiple social, economic, and environmental county-level characteristics were included in our model. Data for our independent variables were drawn from multiple sources including, the CDC, US Census Bureau, US Department of Agriculture (USDA), and US Department of Health and Human Services.

Independent variables included: 1) the percentage of the population living at or below the federal poverty thresholds, 2) the percentage of the labor force that were unemployed, and 3) residential segregation of the poor from the non-poor to tap into the economic context of counties. Data for each of these variables were obtained from the US Census Bureau’s 2005-2009 American Community Survey (ACS) 5-year estimates. While other research has suggested that counties with greater poverty and unemployment experience greater chronic disease prevalence (5,6), we wished to understand whether these relationships maintained between regions of the US.

Measures of the healthcare context of counties included: 4) the percentage of the population without health insurance, 5) the number of physicians per 1,000 people, and 6) the number of outpatient visits per 1,000 people. Health insurance data were drawn from the US Census Bureau’s Small Area Health Insurance Estimates (SAHIE) for 2009. Both physicians and outpatient visits data were taken from the US Department of Health and Human Services Area Health Resources Files (AHRF) for 2009. Drawing from published evidence that has shown the advantageous effect of health insurance and availability of health providers on community health (12), we wanted to test whether inter-regional differences existed in these relationships.

The recreational context of counties was captured by: 7) the age-adjusted percentage of adults (≥20 years) who were physically inactive, 8) the number of fitness and recreation centers per 1,000 people, and 9) an index of natural amenities. The physical inactivity measure was drawn from the CDC’s Diabetes Interactive Atlas, the fitness center data was from the US Census Bureau’s County Business Patterns (CBP), and the natural amenities measure was drawn from the USDA’s Economic Research Service (ERS). Research has shown that the natural environment, aggregate levels of physical inactivity, and access to recreational facilities are each important considerations in understanding community health (13-15). Given this evidence we sought to understand whether there were regional differences in the associations between recreational resources and adult obesity prevalence.

Measures of the food environment included: 10) the percentage of a county’s population living in food desert census tracts and 11) the number of fast food restaurants per 1,000 people. Data for fast food restaurants were drawn from the US Census Bureau’s CBP and the food desert measure was provided by the USDA’s ERS. Access to food outlets has been shown to be related to obesity prevalence; lower obesity prevalence in the case of supermarkets and higher obesity prevalence with greater numbers of fast food restaurants (16,17). We sought to understand whether the food environment was differentially associated with adult obesity prevalence between US regions.

The population structure of counties was captured by: 12) the percentage of families headed by single mothers, 13) the percentage of the population ≥65 years, 14) the percentage of the population African American, 15) the percentage of the population Hispanic, and 16) urban influence using three dummy variables: metropolitan area (reference), micropolitan area, or a non-core area. Urban influence codes were drawn from the USDA’s ERS, while all other population measures were from the US Census Bureau’s 2005-2009 ACS 5-year estimates. Research has shown that these measures each share a significant relationship with adult obesity prevalence when examining the US as a whole (6). However, we were interested in understanding whether these relationships were significantly different between regions of the US.

Last, educational levels were measured by: 17) the percentage of the population ≥25 years without a high school diploma or equivalent. This measure was taken from the US Census Bureau’s 2005-2009 ACS 5-year estimates. Educational attainment has been demonstrated as a critical dimension of community health (12). More specifically, greater levels of educational attainment are related to lower obesity prevalence for all counties in the US (6). We aimed to detect whether this relationship was significantly different between US regions.

Statistical analysis

First, we carried out a Local Indicators of Spatial Association (LISA) analysis to provide a geographic breakdown of contiguous counties that belonged to high- and low-obesity clusters across the US. The LISA results revealed significant regional concentrations of counties characterized by both high and low obesity prevalence suggestive of structural differences across regions related to this outcome (i.e., the existence of spatial obesity regimes) (3,18,19).

Next, we conducted a spatial regime regression analysis to detect the significance of parameter differences across regions (20-22).
This modeling strategy allowed us to test for significant effects of each independent variable on county-level adult obesity prevalence within and between the four major Census Bureau-defined US regions (i.e., Northeast, Midwest, South, and West). The procedure entailed specifying a fully interacted regression model between region and each independent variable (e.g., South × percent pop. poor). More specifically, we repeated regressions of the fully interacted model with regional interactions withheld sequentially for each region.

A number of steps were taken to correctly specify the model. We tested for multicollinearity among our independent variables and found no substantial issues (no variance inflation factor exceeded 4). We also grand mean centered (nation) each independent variable. In addition, because counties are situated in states and states contain varying numbers of counties, we included state fixed-effects to control for county-invariant variables within each state (e.g., state-specific health policies). Last, we included a spatial lag term to address diagnosed issues of spatial autocorrelation present in the dependent variable (Moran’s $I = 0.6$, indicating positive spatial autocorrelation, or the significant clustering of counties with like values). Adjusting for the spatially lagged measure of adult obesity prevalence ensures that results are not biased by shared similarities in obesity levels across neighboring counties (23,24). We utilized GeoDa 1.4.6. for the spatial diagnostics (25). All regression analyses were carried out using IBM® SPSS® Statistics Version 20.

### Results

Table 1 shows that in 2009 the mean prevalence of county-level adult obesity varied by region from 25%, in the West, to 32%, in the South. Figure 1 presents a LISA map of significant high- and low-obesity county clusters within each region using a pseudo $P$-value < 0.05 based on a random permutation procedure (26). The

| Variable | Nation | South | Northeast | Midwest | West |
|----------|--------|-------|-----------|---------|------|
| Dependent variable | | | | | |
| Percent of adults obese | 30.3 (4.2) | 32.0 (3.7) | 27.3 (3.8) | 30.6 (2.9) | 25.3 (4.4) |
| Independent variables | | | | | |
| Economic context | | | | | |
| Percent of pop. poor | 15.6 (6.5) | 18.2 (6.8) | 11.5 (3.8) | 12.9 (5.2) | 14.3 (5.5) |
| Percent of labor force unemployed | 4.1 (1.7) | 4.4 (1.6) | 4.2 (0.9) | 3.8 (2.0) | 4.0 (1.7) |
| Poor/non-poor segregation | 18.8 (10.8) | 18.4 (9.8) | 27.0 (10.3) | 17.9 (11.0) | 18.0 (11.8) |
| Healthcare context | | | | | |
| Percent of pop. uninsured | 18.3 (5.6) | 21.3 (5.2) | 11.8 (2.9) | 14.6 (3.6) | 21.1 (4.8) |
| Number of physicians per 1,000 pop. | 1.5 (1.6) | 1.4 (1.8) | 2.9 (2.9) | 1.3 (1.5) | 1.8 (1.4) |
| Number of outpatient visits per 1,000 pop. | 2,431.2 (3,323.9) | 1,888.7 (3,205.0) | 3,692.1 (4,009.6) | 2,923.4 (3,530.9) | 2,380.3 (2,286.3) |
| Recreational context | | | | | |
| Percent of adults physically inactive | 26.9 (4.9) | 29.3 (4.3) | 24.2 (3.7) | 26.5 (3.8) | 21.2 (4.3) |
| Number of recreation facilities per 1,000 pop. | 0.1 (0.1) | 0.1 (0.1) | 0.1 (0.1) | 0.1 (0.1) | 0.1 (0.1) |
| Natural amenities (low of 1 to high of 7) | 3.5 (1.0) | 3.6 (0.7) | 3.5 (0.6) | 2.7 (0.7) | 5.0 (1.1) |
| Food environment | | | | | |
| Percent of pop. living in a food desert | 17.3 (25.5) | 16.1 (23.3) | 7.7 (10.4) | 19.5 (28.5) | 20.6 (28.8) |
| Number of fast food restaurants per 1,000 pop. | 0.6 (0.3) | 0.6 (0.3) | 0.6 (0.2) | 0.5 (0.3) | 0.6 (0.4) |
| Population structure | | | | | |
| Percent of families headed by single mothers | 9.6 (3.8) | 11.0 (4.2) | 9.5 (2.8) | 8.3 (3.1) | 8.3 (3.2) |
| Percent of pop. aged 65 and older | 15.4 (4.2) | 14.6 (3.8) | 15.0 (2.5) | 16.7 (4.3) | 14.7 (5.1) |
| Percent of pop. African American | 8.9 (14.4) | 16.7 (17.8) | 4.7 (6.3) | 2.1 (4.5) | 1.2 (2.0) |
| Percent of pop. Hispanic | 7.6 (12.8) | 8.7 (14.7) | 5.0 (6.9) | 3.3 (4.9) | 15.9 (16.6) |
| Metropolitan | 0.4 (0.5) | 0.4 (0.5) | 0.6 (0.5) | 0.3 (0.4) | 0.3 (0.5) |
| Micropolitan | 0.2 (0.4) | 0.2 (0.4) | 0.2 (0.4) | 0.2 (0.4) | 0.2 (0.4) |
| Noncore | 0.4 (0.5) | 0.4 (0.5) | 0.2 (0.4) | 0.5 (0.5) | 0.5 (0.5) |
| Educational level | | | | | |
| Percent of adults with less than high school | 17.1 (7.3) | 21.6 (7.0) | 12.5 (3.6) | 13.3 (4.8) | 13.6 (6.1) |
| High obesity (%) | 15.8 | 30.3 | 0.0 | 5.8 | 0.0 |
| Low obesity (%) | 13.5 | 2.4 | 40.6 | 2.6 | 65.7 |
| N | 3,109 | 1,423 | 217 | 1,055 | 414 |

Pop. is an abbreviation for “population.” Mean (standard deviation).
LISA analysis tests the probability that no spatial interdependence exists among neighboring counties in a specified measure (5). In this case the null hypothesis of spatial randomness was rejected. Examining region specific clusters, 30% of counties in the South \((n = 1,423)\) were located in high-obesity clusters, while only 2% of counties were located in low-obesity clusters. For the Northeast \((n = 217)\), no counties were part of a high-obesity cluster and 41% of counties belonged to a low-obesity regional cluster. Fewer obesity clusters were present in the Midwest \((n = 1,055)\), with 6% and 3% of counties belonging to high- and low-obesity clusters, respectively. In the West \((n = 414)\), no counties were part of a high-obesity cluster, while 66% of counties were members of low-obesity clusters.

Motivated not only by the LISA analysis, but also by spatial Chow tests that demonstrated the unequal impact of explanatory variables between each region and across all regions (19,27,28) (Supporting Information Table S1), we next carried out a spatial regime analysis to identify which determinants of obesity prevalence significantly differed between the regions. Table 2 provides results from the spatial regime model. The table shows unstandardized ordinary least squares (OLS) regression coefficients representing the main effects for the region identified in the column heading, controlling for the full range of other region-by-covariate multiplicative interaction terms. Thus, coefficients should be interpreted as the effect of a given variable for a particular region net of the effect of that variable in other regions of the country. For example, the table cell for percent poor in the column labeled “South” is an unstandardized OLS regression coefficient representing the effect of poverty in southern counties, controlling for the effects of poverty in counties in the Northeast, Midwest, and West. Asterisks demarcate the significance of each independent variable within the specified region in the column heading. Significant differences between the region in the column heading and other regions are denoted by the letter superscripts and are indicated by region-by-covariate interaction terms in each model (not shown).

**Northeast**

Hispanic populations were significantly related to lower obesity prevalence in the Northeast and this relationship was stronger in this region compared to each of the other three regions. Additionally, the spatial lag term was not significant in the Northeast, which was significantly different from the positive relationship with obesity prevalence witnessed in each of the other three regions.

**Midwest**

In the Midwest, the impact of unemployed labor force participants was significantly related to higher obesity prevalence and was different relative to the South with the effect being stronger in the Midwest. The positive association between physically inactive adults and obesity prevalence was significantly weaker in the Midwest compared to counties in each of the other three regions.

**West**

Unemployed workers and uninsured populations shared significant positive and negative relationships, respectively, with adult obesity prevalence in the West. These associations were significantly stronger in the West relative to counties in the South. Physically inactive adults also had a significantly stronger association with obesity prevalence in the West compared to the South.

**South**

In the South, residential segregation between poor and non-poor populations was significantly linked to lower obesity prevalence with this effect being stronger from that witnessed in the Northeast and Midwest. African American populations were significantly linked to higher adult obesity prevalence in the South. Importantly,
TABLE 2 Unstandardized OLS regression coefficients from a fully interacted regional model of county-level adult obesity prevalence, 2009

| Variable                                | South (a) | Northeast (b) | Midwest (c) | West (d) |
|------------------------------------------|-----------|---------------|-------------|----------|
| Economic context                         |           |               |             |          |
| Percent of pop. poor                     | 0.020     | -0.028        | -0.010      | 0.013    |
| Percent of labor force unemployed        | 0.018c,d  | 0.446         | 0.346**     | 0.284**a |
| Poor/non-poor segregation                | -0.019ab,c| 0.032a        | 0.006a      | 0.009    |
| Healthcare context                       |           |               |             |          |
| Percent of pop. uninsured                | 0.030d    | 0.054         | -0.006      | -0.081** |
| Number of physicians per 1,000 pop.     | -0.360*** | -0.250**      | -0.331***   | -0.468***|
| Number of outpatient visits per 1,000 pop.| 0.093***  | 0.121*        | 0.073***    | 0.144**  |
| Recreational context                     |           |               |             |          |
| Percent of adults physically inactive    | 0.302**c,d| 0.426**c      | 0.221**ab,d | 0.472**ab,c|
| Number of recreation facilities per 1,000 pop. | -2.106*  | -2.914        | -0.572      | -2.965*  |
| Natural amenities (low of 1 to high of 7) | -0.081    | -0.278        | -0.229*     | -0.228   |
| Food environment                         |           |               |             |          |
| Percent of pop. living in a food desert  | -0.001    | 0.017         | -0.001      | 0.006    |
| Number of fast food restaurants per 1,000 pop. | -0.042    | -0.831        | -0.460      | -0.069   |
| Population structure                     |           |               |             |          |
| Percent of families headed by single mothers | 0.026     | 0.181         | 0.100**     | 0.089    |
| Percent of pop. aged 65 and older        | -0.035c,d | -0.062        | 0.034*      | -0.018   |
| Percent of pop. African American         | 0.072***b,c,d | -0.060a       | 0.016b      | -0.063b  |
| Percent of pop. Hispanic                 | -0.016ab  | -0.191***c,d  | -0.009b     | -0.029b  |
| Metropolitan (ref.)                      | -         | -             | -           | -        |
| Micropolitan                             | 0.169     | -0.346        | 0.009       | 0.081    |
| Noncore                                  | -0.336*   | -0.611        | -0.070      | -0.798*  |
| Educational level                        |           |               |             |          |
| Percent of adults with less than high school | 0.022     | 0.143         | 0.049*      | 0.083*   |
| Spatial lag                              | 0.154***b | -0.011bc,d    | 0.184***b   | 0.130**b |
| Intercept                                | 30.312*** | -             |             |          |
| Adjusted $R^2$                           |           |               |             | 0.754    |

Pop. is an abbreviation for “population.” Model controls for state fixed-effects. Number of outpatient visits per 1,000 pop. coefficient multiplied by 1,000. *P < 0.05; **P < 0.01; ***P < 0.001 indicate significant coefficients that are the main effect of the specified covariate in the region identified in the column heading. a,b,c,d indicate significant (P < 0.05) differences of each independent variable between the region denoted in the column heading and the other regions. For example, for the variable “Percent of labor force unemployed,” the South, which is labeled “a” in the column heading, differed from the Midwest (column c) and the West (column d) but not the Northeast (column b). N = 3,109.

Discussion

The current study aimed to identify significant regional differences in adult obesity prevalence in the US. Our findings demonstrated the existence of spatial regimes of obesity prevalence across US regions. Specifically, the South was identified as a high-obesity spatial regime, while the Northeast and West were shown to be low-obesity spatial regimes. This is a unique contribution to the literature as it shows that obesity in certain regions of the country is structurally different from obesity in other regions.

One notable finding from this research is that the greatest concentration of elevated adult obesity prevalence in the country was in a large contiguous region of counties in the South that spanned Arkansas, Louisiana, Mississippi, and Alabama (Figure 1). This under-scores calls for special attention to the social, economic, political, and culture factors that are linked to poor population health in the “Deep South” (29). Additionally, two secondary notable concentrations of high adult obesity prevalence counties were also shown in Kentucky/West Virginia and North Carolina/South Carolina. These two areas are also part of the US South. This provides further evidence that in terms of concentrated obesity prevalence the South needs to be a focal point for research and public policy.

This study also aimed to explicitly articulate the underlying factors driving regional disparities in adult obesity prevalence. Our results identified a number of significantly different associations between county-level adult obesity prevalence and county features between US regions. In the South, the positive association between African American populations and obesity prevalence is especially pronounced compared to other regions. This stands to reason as African American population density is by far most pronounced in the South. Of the six states with an African American population in
excess of 25% of the total population, all are in the South: Mississippi, Louisiana, Georgia, Maryland, South Carolina, and Alabama (30). Again this suggests the Deep South or “Black Belt” (31) as potential focal points for obesity research and intervention. In the Midwest, as elsewhere, physical inactivity is positively associated with obesity prevalence, but this effect is significantly weaker than in other regions of the country. Why this regional distinction exists is not clear, though the uniform benefit of physical activity across regions is unmistakable. Hispanic populations in the Northeast were particularly relevant for lower obesity prevalence in this region compared to the remainder of the US. This finding is consistent with previous research (6). Compared to the South, the association between unemployed workers and elevated obesity prevalence was much stronger in both the Midwest and West indicating that the deleterious consequences of unemployment on community health is particularly heightened in these two regions.

Also of importance are those factors that operated uniformly across regions. Two measures of the healthcare context held significance across regions, albeit in opposite directions. Physician density was significantly negatively correlated with obesity prevalence in all areas of the country, suggesting increasing physician supply in underserved areas is warranted. Conversely, outpatient visits were uniformly associated with higher obesity prevalence, perhaps signaling greater demands for care associated with the range of chronic health problems related to obesity. Of note are also those factors that were uniformly insignificant across all regions in the presence of other predictors. These include poverty, indicators related to the food environment, and living in small town settings (micropolitan areas) relative to metropolitan areas. Importantly, this is not to suggest that a factor like poverty does not matter, just that in the presence of a full range of other predictors it is not the influence of low-income populations that stands out so much as attendant factors.

These regional differences are consonant with other public health research that has highlighted unique geographic regions of both lower and elevated levels of chronic diseases (1-3). Given this evidence, interventions or policies aimed at addressing chronic diseases measured at lower levels like neighborhoods or higher levels like states (37,38). Finally, this study is limited by the fact that it must rely on model-based estimates produced by the CDC based on BRFSS data. Despite the advantages of BRFSS data because of its large sample size and wide geographic coverage, it relies on self-reported height and weight which is known to be associated with underestimates in obesity prevalence. Recent research has cautioned that geographic differences in the magnitude of this bias may be less pronounced in some regions of the country (i.e., the southeast US) and more pronounced in others (i.e., the north central US) (39). The region-specific approach taken in this study helps to ameliorate this concern. However, in the end, there is no question that directly measured population health census data would be invaluable for obesity research, policy, and intervention. Unfortunately, it currently does not exist in the US.

This study showed that regional disparities in adult obesity prevalence exist at a significant level between regions of the US, and that county features mattered in shaping this disparity. This study also suggests that obesity is particularly burdensome in the US South, which has economic and public health implications for addressing this epidemic. Continued research focusing on space and place in relation to obesity prevalence should further elaborate distinctive areas of the US in need of tailored interventions and public health policies and the unique factors linked to obesity across areas of the country.

© 2014 The Obesity Society

References
1. Barker LE, Kirtland KA, Gregg EW, Geiss LS, Thompson TJ. Geographic distribution of diagnosed diabetes in the U.S.: a diabetes belt. Am J Prev Med 2011; 40:434-439.
2. Liao Y, Greenland KJ, Croft JB, Keenan NL, Giles WH. Factors explaining excess stroke prevalence in the US Stroke Belt. Stroke 2009;40:3336-3341.
3. Michimi A, Wimberly MC. Spatial patterns of obesity and associated risk factors in the conterminous U.S. Am J Prev Med 2010;39:e1-e12.
4. Gregg EW, Kirtland KA, Cadwell BL, et al. Estimated county-level prevalence of diabetes and obesity—United States, 2007. JAMA 2010;303:933-935.
5. Shrestha SS, Kirtland KA, Thompson TJ, Barker LE, Gregg EW, Geiss LS. Spatial clusters of county-level diagnosed diabetes and associated risk factors in the United States. Open Diabetes J 2012;5:29-37.
6. Slack T, Myers CA, Martin CK, Heimylis SB. The geographic concentration of U.S adult obesity prevalence and associated social, economic, and environmental factors. Obesity 2014;22:868-874.
7. United States Census Bureau. Geographic Terms and Concepts—Census Divisions and Census Regions. July 22, 2013. Last accessed October 29, 2013. Available at: https://www.census.govgeo/reference/pts/gc_census_divreg.html.
8. Center for Disease Control and Prevention (CDC). Centers for Disease Control and Prevention Diabetes Interactive Atlas. 2009. Last accessed October 29, 2014. Available at: http://www.cdc.gov/diabetes/atlas/.
9. Centers for Disease Control and Prevention (CDC). Behavioral Risk Factor Surveillance System (BRFSS). September 29, 2014. Last accessed October 29, 2014. Available at: http://www.cdc.gov/brfss/index.htm.

10. United States Census Bureau. Population Estimates. June 26, 2014. Last accessed October 29, 2014. Available at: http://www.census.gov/popest/index.html.

11. Cadwell BL, Thompson TJ, Boyle JP, Barker LE. Bayesian small area estimates of diabetes prevalence by U.S. county, 2005. J Data Sci 2010;8:173-188.

12. Hillemeier MM, Lynch J, Harper S, Casper M. Measuring contextual characteristics for community health. Health Serv Res 2003;38:1645-1718.

13. Diez Roux AV, Evenson KR, McGinn AP, et al. Availability of recreational resources and physical activity in adults. Am J Public Health 2007;97:493-499.

14. Dwyer-Lindgren L, Freedman G, Engell RE, et al. Prevalence of physical activity and obesity in US counties, 2001-2011: a road map for action. Popul Health Metr 2013;11:7.

15. von Hippel P, Benson R. Obesity and the Natural Environment Across US Counties. Am J Public Health 2014;104:1287-1293.

16. Morland KB, Evenson KR. Obesity prevalence and the local food environment. Health Place 2009;15:491-495.

17. Ford PB, Dziewaltowski DA. Disparities in obesity prevalence due to variation in the retail food environment: three testable hypotheses. Nutr Rev 2008;66:216-228.

18. Chi G, Zhu J. Spatial regression models for demographic analysis. Popul Res Policy Rev 2008;27:17-42.

19. Baller RD, Anselin L, Messner SF, Deane G, Hawkins DF. Structural covariates of U.S. county homicide rates: incorporating spatial effects. Criminology 2001;39: 561-588.

20. Curtis KJ, Voss PR, Long DD. Spatial variation in poverty-generating processes: Child poverty in the United States. Soc Sci Res 2012;41:146-159.

21. Shoff C, Yang TC. Spatially varying predictors of teenage birth rates among counties in the United States. Demogr Rev 2012;27:377-418.

22. O’Connell HA, Shoff C. Spatial variation in the relationship between hispanic concentration and county poverty: a migration perspective. Spatial Demogr 2014;2:30-54.

23. Schultz J, Elliott J. Natural disasters and local demographic change in the United States. Popul Environ 2013;34:293-312.

24. Ward MD, Gleditsch KS. Spatial Regression Models. Thousand Oaks: Sage Publications; 2008.

25. Anselin L, Syabri I, Kho Y. GeoDa: an introduction to spatial data analysis. Geogr Anal 2006;38:5-22.

26. Anselin L. Exploring spatial data with GeoDa. 2005. Last accessed October 29, 2014. Available at: https://geodacenter.asu.edu/system/files/geodaworkbook.pdf.

27. Anselin L. Spatial dependence and spatial structural instability in applied regression analysis. J Regional Sci 1990;30:185-207.

28. Chow GC. Test of equality between sets of coefficients in two linear regressions. Econometrica 1960;28:591-605.

29. Goldhagen J, Remo R, Bryant T III, et al. The health status of southern children: a neglected regional disparity. Pediatrics 2005;116:e746-e753.

30. Rastogi S, Johnson TD, Hoefl EM, Drewery J, Malcom P. The Black Population: 2010. 2010 Census Briefs. Report Number C2010BR-06. Washington, D.C.

31. Wimberly DW. Quality of life trends in the Southern Black Belt, 1980-2005: a research note. J Rural Soc Sci 2010;25:103-118.

32. Cummins S, Curtis S, Diez-Roux AV, Macintyre S. Understanding and representing ‘place’ in health research: a relational approach. Soc Sci Med 2007;65:1825-1838.

33. Mobley LR. What are spatial data? When are they sufficient? Spatial Demogr 2013;1:120-130.

34. Osypuk TL, Acevedo-Garcia D. Beyond individual neighborhoods: a geography of opportunity perspective for understanding racial/ethnic health disparities. Health Place 2010;16:1113-1123.

35. United States Department of Health and Human Services. Healthy people 2020 framework. October 29, 2014. Last accessed October 29, 2014. Available at: http://www.healthypeople.gov/2020.

36. Boardman JD, Onge JMS, Rogers RG, Denney JT. Race differentials in obesity: the impact of place. J Health Soc Behav 2005;46:229-243.

37. Saib M-S, Caudeville J, Carre F, Garry O, Truexon A, Cicolella A. Spatial relationship quantification between environmental, socioeconomic and health data at different geographic levels. Int J Environ Res Public Health 2014;11:3765-3786.

38. Kwan M-P. The uncertain geographic context problem. Ann Assoc Am Geographers 2012;102:958-968.

39. Le A, Judd SE, Allison DB, et al. The geographic distribution of obesity in the US and the potential regional differences in misreporting of obesity. Obesity 2014;22: 300-306.