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Using simulated data to investigate the spatial patterns of obesity prevalence at the census tract level in metropolitan Detroit

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ABSTRACT

Obesity is a serious public health problem in the United States. It is important to estimate obesity prevalence at the local level to target programmatic and policy interventions. It is challenging, however, to obtain local estimates of obesity prevalence because national health surveys such as the Centers for Disease Control and Prevention (CDC) Behavioral Risk Factor Surveillance System (BRFSS) are not designed to produce direct estimates at the local levels (e.g. census tracts) due to small population samples and the need to preserve individual confidentiality. In this study we address the problem of estimating local obesity prevalence rates by implementing a spatial microsimulation modeling technique to proportionally replicate the demographic characteristics of BRFSS respondents to census tract populations in metropolitan Detroit. Obesity prevalence rates are examined for high and low spatial clusters and studied in relation to the U.S. Department of Agriculture's (USDA) measures of low-income neighborhoods and local food deserts and CDC's measure of healthy and less healthy food environments currently used to target obesity reduction initiatives. This study found that obesity prevalence was largely clustered in the City of Detroit extending north into contiguous suburbs. The spatial patterns of highest obesity prevalence tracts were most similarly aligned with USDA-defined low-income tracts and CDC's less healthy food tracts. The locations of USDA's food desert tracts rarely overlapped with the highest obesity prevalence tracts. This study demonstrated a new methodology by which to assess local areas in need of future obesity interventions.

Introduction

Obesity is a serious public health problem in the United States. Obesity is described as abnormal or excessive body fat accumulation that may cause negative health outcomes. The 10th revision of the International Statistical Classification of Diseases and Related Health Problems (ICD-10) published by the World Health Organization (WHO) (2011) classifies obesity as an “Endocrine, Nutritional and Metabolic disease (E65-E68).” While obesity is itself a serious chronic disease it is also an underlying cause of comorbidity, including but not limited to cardiovascular disease, Type-II diabetes, osteoarthritis, stroke and certain types of cancers (Finkelstein et al., 2012; Fish, Ettner, Ang, & Brown, 2010). The body mass index or BMI is a measure of adiposity using the weight and height of adult individuals—i.e., the individual's weight in kilograms divided by the square of one's height in meters. Since 1998 the Centers for Disease Control and Prevention (CDC) has followed the WHO BMI guidelines (WHO, 1998) to define adult obesity as 30 (kg/m^2) or greater. A BMI range from 25.0 to 29.9 kg/m^2 is considered overweight. The normal BMI range for adults is 18.5–24.9 kg/m^2 (Kuczmarski & Flegal, 2000).

In 1998 approximately 14% of American adults were reported to be obese. In 2011–2012, 35% of adults were reported to be obese and another one-third of adults (33%) were reported to be overweight, demonstrating the fast rise in adult obesity prevalence in the United States (Fryar, Carroll, & Ogden, 2012; Ogden, Carroll, Kit, & Flegal, 2014). Research based on linear time-trend forecasts reports that approximately half of U.S. adults (51%) will be obese by 2030 (Finkelstein et al., 2012). Masters et al. (2013) also found that between 1986 and 2006 approximately 18% of premature deaths in adults aged 40–85 years in the U.S. were associated with obesity or obese-related comorbidities. Obesity also poses a heavy financial burden on public health spending in the United States. The

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American Public Health Association (APHA) estimated that $300 billion annually was spent on obesity and obesity-related problems in 2012 (APHA, 2012). Yang and Zhang (2014) estimated the additional cost of obesity could increase from $48 to $66 billion each year if the current obesity prevalence trend continues.

Challenges of estimating local obesity prevalence rates

For obesity researchers and public health professionals it is important to uncover individual and environmental risk factors for obesity at a local level in order to recommend targeted intervention and prevention programs to reduce high obesity and maintain low obesity prevalence rates. However it is challenging to estimate obesity prevalence at local geographic scales because public health surveys are designed to collect health and related behavioral information at the state and national scales. For example, the Behavioral Risk Factor Surveillance System (BRFSS) is a national health survey conducted by the CDC each year. The BRFSS is collected by sampling residents in counties, public health districts or other sub-state geographies (CDC, 2013a). The smallest geographic scale publicly accessible in the BRFSS is the county-level but for small sampled counties the geographic information (e.g. county code) is often suppressed to ensure the privacy of respondents. Obesity prevalence rates therefore, cannot be estimated in sampled counties where data is suppressed, non-sampled counties (such as rural areas), and local areas below the county scale. To address this challenge, this study will utilize a spatial microsimulation technique to proportionally replicate the demographic characteristics of respondents in the BRFSS to the census tract geography. By doing so it becomes possible to explore the spatial patterns of obesity prevalence in relation to environmental conditions at a local scale.

Spatial microsimulation

Microsimulation was originally introduced by Orcutt (1957) as a modeling technique to generate large synthetic population data to analyze the impacts of population changes on government policies and vice versa (Ballas, Rossiter, Thomas, Clarke, & Dorling, 2005). Over the subsequent decades, microsimulation gained more attention among social scientists as a cost-effective method to generate and analyze policy, especially to examine the interaction of tax policy and demographic changes at the individual and household levels (Ballas et al., 2005; Rahman, 2009). While microsimulation itself focuses on estimating the effect of population change, spatial microsimulation aims to create synthetic population datasets for small geographic areas where existing survey and/or census data are unavailable (Rahman, 2009).

Two different datasets are involved in spatial microsimulation. The first is survey data (e.g., BRFSS) which has detailed demographic information on the respondents (e.g., sex, age and education) and survey purpose (e.g., smoking behaviors and BMI) but detailed geographic information is unobtainable. The second dataset needed to conduct spatial microsimulation is census data that has detailed demographic information at the local geographic scale but lacks health information (e.g., obesity). Using common "demographic" information in the BRFSS and census data, spatial microsimulation is used to generate a simulated synthetic population dataset of obesity estimates at the local level.

There are a growing number of health and population studies using spatial microsimulation. For example, Tomintz, Clarke, and Rigby (2009) used the General Household Survey, Health Survey for England and the United Kingdom (UK) census to estimate smoking rates at the output area level (the lowest geographical unit for census estimates) in Leeds, UK to optimize location(s) for smoking interventions. Tanton (2011) examined the spatial patterns of poverty rates at the Statistical Local Area level (the lowest geographical unit for census estimates available in Australia) using national surveys of Income and Housing and census housing and population data. More recently, Morrissey, O'Donoghue, Clarke, and Li (2013) investigated the spatial variation in acute hospital utilization and related micro-level factors in Ireland using the Living in Ireland Survey and the Irish Small Area Population Statistics data. These authors found that increasing age and long-term illness contributed to the spatial variation in hospital service demand in Ireland.

There are a few studies using spatial microsimulation to study obesity. Edwards, Clarke, Ransley, and Cade (2010) estimated childhood obesity prevalence in census wards in Leeds, UK using the National Child Health Computer System and the UK census. Obesity prevalence rates were studied in relation to local environmental risk factors including neighborhood safety, fruits and vegetables consumption, Internet access, and access to supermarkets. The authors found that these local environmental characteristics impacted local obesity prevalence rates differently in high and low household income census wards. Cataife (2014) utilized the Brazil Family Expenditure Survey and the Brazil census to create a simulated data set of obesity prevalence at the local level in Rio de Janeiro, Brazil. This study found that at the local level, Rio de Janeiro was experiencing the dual burden of high malnutrition and high obesity prevalence, explained by household income, physical activity and food intake habits. To our knowledge there is no study that has utilized a spatial microsimulation approach to study obesity prevalence in the United States. These prior studies highlight the value of investigating the spatial microsimulation technique to improve our understanding of local obesity prevalence rates in relation to environmental characteristics to improve our understanding of the rise in obesity.

Obesity risk factors

Prior to conducting spatial microsimulation it is important to have a good understanding of the demographic characteristics of the obese population in order to most appropriately simulate the same demographic characteristics in the local-population census. In the United States, adult women have higher obesity prevalence rates compared to adult men (U.S. Department of Health and Human Services, 2011). While middle-aged women (40–59 years) have higher obesity prevalence rates than younger women, men aged 60 years and older have higher obesity prevalence rates than younger men (Flegal, Carroll, Ogden, & Curtin, 2010). Non-Hispanic Blacks have higher obesity prevalence rates compared to non-Hispanic Whites (Frank, Andresen, & Schmid, 2004; Robert & Reither, 2004). Importantly, education has been shown to be protective of obesity with college graduate males and females having lower obesity prevalence rates than high school graduate males and females (Ogden and Carroll, 2010).

Environmental risk factors for obesity include urban sprawl, inadequate built space for physical activity, private vehicle use, transit-friendly land use planning, neighborhood safety (Congdon, 2014; Ewing, Schmid, Killingsworth, Zlot, & Raudenbush, 2003; Fish et al., 2010; Frank et al., 2004; Rundle et al., 2008) and the composition of neighborhood food environments (Chen & Yang, 2014; Hallett & McDermott, 2011; Morland, Roux, & Wing, 2006). Obesity researchers have extensively investigated the impacts of food environments on obesity and adverse health outcomes in relation to socio-economic and cultural variables (Vojnovic et al., 2013; 2014). For example, Morland et al. (2006) using survey data in Maryland, Minnesota, Mississippi and North Carolina (1993–1995) found that residents living in a census tract with one