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Evaluating the relationship between urban environment and food security in Georgia's older population

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ABSTRACT

While food insecurity in older adults is closely linked to economic circumstances and functional limitations, research has shown that the physical and social environment can have a significant influence on food insecurity (Carter, Dubois, & Tremblay, 2014). This paper reports on an ongoing research collaboration with Georgia's Division of Aging Services (DAS) and the University of Georgia. We used data from the Georgia Aging Information Management System (AIMS), which manages information on current or waitlisted clients in the state's aging services and programs ($n = 38{,}812$). We geocoded this data and added residence in a USDA defined food desert and whether the place of residence was in a rural area, urban cluster, new suburb, post-war suburb, or core urban area. The latter classification is a new measure developed from historic census data and is the main focus of this paper. We explored the relationships of these variables to rates of food insecurity through descriptive statistics and a logistic regression model. Our analysis showed a modest but significant positive relationship between food insecurity and residence in core urban areas (OR 1.27, 95% CI:1.17–1.38) and urban clusters (OR: 1.15, 95% CI: 1.08–1.23).

Introduction

The population of older individuals in the United States is growing at a rapid pace, with its share of the total U.S. population expected to double in the next fifty years (U.S. Census Bureau, 2012b). Approximately 91% of older adults have one chronic health problem, and 73% of them have at least two chronic conditions (Anderson, 2010). These factors can impede mobility and strain limited budgets, affecting households' food access. In 2009, households with older individuals had a food insecurity rate of 7.5%, a figure which rose to 8.8% in 2012 (Coleman-Jensen, Nord, & Singh, 2013; Nord, Coleman-Jensen, Andrews, & Carlson, 2010). These rates are below the national average (14.5%) but still demonstrate the need for research on social and environmental drivers of the food insecurity within this growing demographic.

While food insecurity in older adults is closely linked to economic circumstances and functional limitations, a growing body of research has shown that the physical and social environment can have a significant influence (Carter, Dubois, & Tremblay, 2014). Rather than examine individual or household level factors, this research has focused on social capital, the urban/rural divide, and the impact of the food environment (Bartfeld, Ryu, & Wang, 2010; Bernell, Weber, & Edwards, 2006; Sharkey, Johnson, & Dean, 2010). However, a recent review by Carter et al. (2014) highlighted inconsistent findings in this literature. While many studies found that the physical and social environment matters to rates of food insecurity, the exact nature of that relationship, as well as differential effects among population subgroups, is still not adequately understood. For older populations, who are prone to isolated living conditions and limited incomes, differences in the neighborhood environment may have a unique impact on household food security by shaping residents' abilities to travel to and purchase affordable, healthy foods.

This paper reports on an ongoing research collaboration with Georgia's Division of Aging Services (DAS) and the University of Georgia. We used data from the Georgia Aging Information Management System (AIMS), which lists current or waitlisted clients in the state's aging services program ($n = 38{,}812$). We geocoded this data and added residence in a USDA defined food desert and historical urbanized area for place of residence. The latter classification is a new measure developed from historic census data and is the main focus of this paper. We analyzed the relationships of these variables to the probability of food insecurity among DAS clients

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through descriptive statistics and a logistic regression model. We analyzed the results of this model for spatial bias using global and local indicators of spatial autocorrelation. Through the use of a statewide dataset and replicable measures of neighborhood form and food environment, this analysis was designed to strengthen understanding of environmental influences on food insecurity among older population.

Background

Through standardized questionnaires, USDA assesses four levels of food security: high, marginal, low, and very low. These lowest two categories are often combined into a single classification of food insecure (Nord et al., 2010, p. 3). Food insecurity has several nutritional and health consequences, including poor dietary intake, unhealthy body weight, poor self-reported health, multi-morbidity, psychological problems such as depression and anxiety, and poor cognitive and physical function (Holben, 2010; Lee, Fischer, & Johnson, 2010). For elderly individuals living alone, that rate in 2012 was 9.1%, compared to a national mean of 14.5% (Coleman-Jensen et al., 2013). Older adults, though, have uniquely challenging circumstances, including increased healthcare burden due to multi-morbidity and polypharmacy (Bhargava, Lee, & Jain, 2012), increasing cognitive and physical limitations (Burns, Bentley, Thornton, & Kavanagh, 2011), and social isolation, all of which increase the odds of food insecurity in this population. These issues augment broader factors that drive food insecurity, including poverty (Holben, 2010), gender (Ivers & Cullen, 2011), and race (Coleman-Jensen et al., 2013, p. 13).

Ecological models of public health suggest that environmental factors, such as the built environment and food accessibility, may also play a key role in food insecurity rates (McLeroy, Bibeau, Steckler, & Glanz, 1988). One recent review of literature linking food insecurity found 18 studies with this approach (Carter et al., 2014). The food environment, most often measured as distance to the nearest supermarket, had a positive effect on food security in half of the eight studies that addressed it. The urban environment can also play a significant role. Among these studies, rural areas were generally seen as protective against food insecurity when compared against urbanized areas (Bartfeld et al., 2010). More walkable neighborhoods resulted in lower levels of food insecurity among elderly New York residents (Chung et al., 2012), and another recent review similarly found that street design, neighborhood safety, and planned green spaces all enhance the mobility of older individuals, a potential key factor in individuals' food shopping ability (Rosso, Auchincloss, & Michael, 2011).

Our research builds on this work, using a measure that divides urbanized areas into four distinct zones. We can thus identify the association between varying urban environments and food insecurity. Our project also analyzed the specific impact of the food environment on food insecurity, with results for this analysis detailed in another paper (Lee, Shannon, & Brown, in press). Through analysis of both descriptive statistics and spatial statistical models, we develop a stronger understanding of the environmental factors affecting food insecurity for older populations.

Setting, data, and methods

This research focuses on Georgia, whose statewide food insecurity rate in 2010–2012 averaged 16.9% (USDA Economic Research Service, 2012). Georgia includes one major metropolitan area in Atlanta, several smaller cities such as Columbus and Augusta, and a large rural population. According to the most recent data from the American Community Survey, Georgia's population is predominantly white (non-Latino) (55%), African-American (31%), and Latino (9.2%). Individuals 65 and older make up 11.5% of the state's population, and Georgia's poverty rate is 17.4%, three percent higher than the national average (U.S. Census Bureau, 2012a).

Our primary data for this study came from the Georgia Aging Information Management System (GA AIMS). These data listed all individuals receiving services or with active applications from the Georgia DAS from 2011 to 2014 ($n = 51{,}283$). These records contained data on a number of key factors, including food security status, gender, age, race, marital status, and living situation. Food security status was assessed using a validated modified six-item U.S. Household Food Security Survey Module (Lee, Johnson, & Brown, 2011) measuring household food insecurity within the last 30 days. These records also included clients' scores on two measures of physical function, Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL), which measure behaviors ranging from eating and bathing to managing money and preparing meals. These data were geocoded using ESRI's ArcGIS software. ESRI's World Geocode Service was used to obtain point or street level matches for most records, with the remainder being done manually using Google Maps. Records for which no clear match could be found or which fell outside state boundaries were excluded ($n = 2634$). Some excluded records also lacked a response for key controlling variables, such as race, household composition, or poverty status ($n = 9837$). The resulting dataset contained full records for 38,812 clients throughout the state (76% of the total study population). As these data were comprised of individual records, they were analyzed as points within GIS software.

Two auxiliary datasets were used to create additional variables for each client. First, data on the food environment was downloaded from the USDA's Food Access Research Atlas (USDA Economic Research Service, 2014), which measures food accessibility by identifying census tracts where more than 1/3 of the population is a mile or more from a supermarket in urban areas and 10 miles or more away in rural areas. Similarly, low-income areas are defined based largely on the percentage of the tract's population living below the poverty line. Combining these measures creates a low-income, low access (LILA) designation that we used to create a binary variable for each individual (in/not in a LILA tract).

Second, we created historically contextualized subclassifications for urbanized areas. The U.S. Census defines these areas as having more than 50,000 residents and population densities greater than 1000 people per square mile (U.S. Dept. of Commerce, 2011). GIS data on urbanized areas are available for the 1990 and 2010 census years. We created two subclassifications for areas urbanized between these two dates: (1) recent suburbs, found on the fringe of older urban areas and (2) urban clusters, which contain no older cores and relatively small total populations. Suburban areas grew rapidly in the period after 1950 (Jackson, 1985), making this year a useful break in our classification, but the Census contains no data on urbanized areas for that time. As a result, urbanized area boundaries for 1950 were recreated using the 1970 decennial census tract level variable for housing units built prior to 1950. From this data, we estimated population density at the tract level, assuming three individuals per household. We used these estimates to define urbanized areas using the criteria listed above. The resulting dataset (Fig. 1) allows us to classify urban areas as core urban (pre-1950), post-war suburban (1950–1990), recent suburban (post-1990, bordering older areas), and urban clusters (post-1990, with no older core).

Based on these data, we developed a logistic regression model predicting food security status, a dichotomous variable, for DAS clients. Unlike OLS models, logistic models output the probability of the dependent variable. Our model can be described as: