The Suburbanization of Food Insecurity: An Analysis of Projected Trends in the Atlanta Metropolitan Area

Jerry Shannon, Department of Geography & Department of Financial Planning, Housing, and Consumer Economics, University of Georgia

Mathew Hauer, Carl Vinson Institute of Government, University of Georgia

Alexis Weaver, Community Impact Manager, Atlanta Community Food Bank

Sarah Shannon, Department of Sociology, University of Georgia

This is an Accepted Manuscript of an article published by Taylor & Francis in the Professional Geographer Science in March 2017, available online:
https://www.tandfonline.com/doi/abs/10.1080/00330124.2017.1325751

Abstract

Although general patterns of food insecurity in the U.S. are known, few studies have attempted to estimate small area food security or account for ongoing socioeconomic changes. Here we address these issues by producing small area estimates of food insecurity in the Atlanta metropolitan area using two methodologies: fixed effects modeling and demographic metabolism. In both cases, we use county level data from the Current Population Survey to determine the association between food insecurity and demographic predictors. These associations are then applied to tract level data from the 2009-2013 American Community Survey and projected data for 2020 to create small area estimates of food insecurity. We find broad consensus between our two methods. For both time periods, food insecurity is highest in southern sections of the city of Atlanta and its neighboring suburbs. Projections to 2020, however, show food insecurity rates are projected to increase in outer ring suburbs east and west of the city while decreasing in the urban core. These results highlight the need to further adapt anti-hunger efforts for often sprawling suburban communities, where poverty rates are increasing but spatial mismatch combined with poor transit access may hinder access to food assistance.

Keywords: food insecurity, suburbanization of poverty, spatial mismatch, Atlanta

---

Food security—defined by the U.S. Department of Agriculture as access "at all times to enough food for an active, healthy life" (Coleman-Jensen 2015)—plays a foundational role in households' health and welfare. Recent research finds that low food security—or food *insecurity*—is correlated with depression and developmental disorders (Carter, Dubois, and Tremblay 2014; Heflin, Siefert, and Williams 2005; Kirkpatrick, McIntyre, and Potestio 2010; Slopen et al. 2010), poorer nutritional intake (Leung et al. 2014), weight gain, and other chronic diseases (Laraia 2012; Seligman, Laraia, and Kushel 2010). While these studies focus on the health outcomes connected to food insecurity, it is important to note that food insecurity is itself the product of multiple overlapping economic and social relations at a variety of scales (Sonnino, Marsden, and Moragues-Faus 2016; Jarosz 2014). These include, for example, systems of agricultural production and distribution, local and global labor markets, and systems of social assistance.

According to the Current Population Survey (CPS), the national rate of food insecurity in 2014 was 14 percent (Coleman-Jensen et al. 2015). A number of studies have identified demographic characteristics associated with higher than average rates. Coleman-Jensen et al. (2011, 13) identify high national rates of food insecurity for households in poverty (40 percent), households with young children (20 percent), and those headed by a single parent, especially a single woman (35 percent) (see also Harris et al. 2014; Mayer et al. 2014). African-Americans (26 percent) and Hispanics (22 percent) also had rates well above the national average. A review by the non-profit Research Triangle Institute (2014) identified other populations at high risk for food insecurity: recent migrants and refugees, those with a disability, and those with other serious medical conditions.

The populations most at-risk for food insecurity have historically been clustered near the city center in U.S. urban areas, and many social services providing food assistance have located in or near these neighborhoods. Yet research over the last two decades has shown the most rapid increases in poverty—closely correlated with food insecurity—have occurred in suburban neighborhoods (Anacker 2015; Kneebone and Berube 2013; Kneebone and Garr 2010). The causes of this shift are complex, including gentrification in the urban core, changing patterns of low wage employment and affordable housing, and an increase in the number of immigrants directly settling in suburban communities (Kneebone and Berube 2013). While suburbs have never been as racially or economically homogeneous as depicted in popular media (Lassiter and Niedt 2013; Pooley 2015), the suburbanization of poverty within the U.S. has dramatically reshaped many communities. In these often sprawling neighborhoods, spatial mismatch—where individuals live in neighborhoods far from work or necessary social services—can further complicate the lives of food insecure households, making it difficult to access food assistance or do routine shopping (Allard 2009; Blumenberg 2004; Cooper et al. 2012; Li, Campbell, and Fernandez 2013). Research identifying shifting patterns of food insecurity in cities and their suburbs can identify where geographically targeted interventions may be most beneficial.

Studying changing patterns of food security at the neighborhood scale is complicated by a lack of readily accessible data. Some research has adapted food security questionnaires for use with local communities (Chung et al. 2012; Harris et al. 2014; Kalichman et al. 2010; Lee, Shannon, and Brown 2014; Mayer et al. 2014). While useful, these studies are labor intensive and expensive, often producing just a single cross sectional sample for one narrowly targeted region or group. Other research has produced county level estimates using statistical models with existing secondary demographic data (Bartfeld and Dunifon 2007). One recent analysis, supported in part by the national organization Feeding America, used fixed effects models with existing CPS data to assess the association between relevant demographic variables and food insecurity rates (Gundersen, Engelhard, and Waxman 2014). Model coefficients were then applied to county data from the American Community Survey (ACS) to produce county level food insecurity estimates. These estimates can be reproduced each year, highlighting local trends and informing strategic planning decisions for local agencies. Still, within urban areas, county level estimates are often too coarse to capture incremental change in food insecurity at the neighborhood level, especially when identifying differences between urban and suburban areas. Neighborhood level estimates can provide better insight on localized changes on the prevalence of food insecurity, illuminating important, but nuanced, shifts.

Completed in partnership with the Atlanta Community Food Bank, our analysis provides this local scale analysis for the Atlanta metropolitan area, identifying the existing prevalence of and projected changes to food security rates at the census tract level. Using census data from both the CPS and ACS we apply two different methodological approaches, one based on fixed effects modeling and the other using demographic metabolism, to create tract level estimates (Gundersen et al. 2014; Lutz 2012). We show how existing infrastructure related to public transit and available food assistance may amplify the harmful effects of food insecurity where spatial mismatch is greatest and growing. Our research contributes to scholarship on the changing geography of poverty in American cities and informs future planning efforts for local anti-hunger agencies and activists.

Setting, Data, and Methods

Our analysis, outlined in Figure 1, makes use of two estimation methods and several sources of data. Following Gundersen et al. (2011), we first employ fixed effects modeling to identify relationships between food insecurity and several demographic variables using existing county level data from the

Current Population Survey. We then apply the coefficients from these models to existing tract level data from the American Community Survey (2009-2013) and projected tract level census data (to 2020) to produce food insecurity estimates. Our second approach, demographic metabolism, identifies food insecurity in the CPS data for age stratified racial subgroups and applies these rates to current and projected tract level census data. By using two different approaches to estimating food insecurity, we control for possible errors unique to either approach.

Given the uncertainty in any estimation, our analysis focuses on broad trends across the Atlanta metropolitan area. In addition to visualizing our results, we also use local indicators of spatial autocorrelation (LISA) to identify regions with significantly autocorrelated high and low values for both current food insecurity rates and projected changes to those rates by 2020. We also compare our results to public transit infrastructure and existing food pantries to assess any growth in spatial mismatch for food insecure households.

Figure 1: Outline of process used for tract estimation

[Figure 1 about here]

Setting

Our study area is the Atlanta-Sandy Springs-Roswell metropolitan statistical area (MSA), defined by boundaries from the U.S. Census (U.S. Census Bureau 2016a). In 2015, the Atlanta MSA had a population of approximately 5.7 million, 9th largest in the country (United States Census Bureau 2015). This figure reflects an increase of 5 percent compared to the estimated 2010 population. According to ACS data, residents of this region are slightly younger than the U.S. average, with a median age of 35.4 compared to the national median of 37.4 (U.S. Census Bureau 2015). The Atlanta

MSA has a higher percentage of non-white residents than the country as a whole. While 74 percent of U.S. residents are classified as Non-Hispanic White, only 56 percent of Atlanta area residents are classified in this way (U.S. Census Bureau 2015). Conversely, 33 percent of the area's residents are classified as African-American alone, notably higher than the national rate of 13 percent. Median household income in the Atlanta MSA is $56,618, similar to the national figure of $53,412 (U.S. Census Bureau 2015).

Like most U.S. metropolitan areas, income distribution across the MSA is highly segregated. In the affluent northern suburb of Alpharetta, median household income is $87,837 and the reported poverty rate is 5.1 percent. In the city of East Point, just south and west of Atlanta, median household income is $39,433 and the reported poverty rate is 27.1 percent (U.S. Census Bureau 2015). Fulton County's Gini coefficient—a statistic often used to measure economic inequality—is 0.53, showing higher disparities than the national figure of 0.48 (U.S. Census Bureau 2015). Racial segregation follows a similar pattern to income, with high concentrations of white populations directly north of Atlanta, and largely African-American populations in the southern half of the metro area (Holloway, Wright, and Ellis 2012). Atlanta also fits the national trend of increasing suburban poverty. The population of suburban Gwinnett County grew from 588,448 in 2000 to 842,901 in 2014, a 43 percent increase (U.S. Census Bureau 2015). During the same time, the county's poverty rate increased nearly threefold, from 4 percent to 11 percent (U.S. Census Bureau 2015).

Demographic variables associated with food insecurity

In phase one of our analysis, we use publically available CPS data for counties in two census regions most similar to our study area in demographic composition: the East South Central and South Atlantic (U.S. Census Bureau 2016b). We downloaded CPS data on the variables listed below from 2009, the first year all variables of interest were present, until 2013. County level CPS data can vary in quality, and our initial set of 81 counties was reduced to 69 when we removed counties with outlying values and high year to year variability, resulting in a total of 345 county-years for analysis

Each December, the CPS includes a Food Security Supplement, a series of questions designed to assess households' ability to meet their basic dietary needs (Coleman-Jensen, Gregory, and Singh 2014). The Food Security Supplement was first used by the U.S. Department of Agriculture (USDA) in 1996, and has provided yearly data since that time. The USDA classifies individual respondents into one of four categories: high food security, marginal food security, low food security, and very low food security. Studies commonly group the latter two categories into a single category, labeled "food insecure" (Coleman-Jensen et al. 2014; Sattler and Lee 2013). We likewise used this condensed classification as our variable of interest. We then assessed the associations between food insecurity and demographic variables provided by the CPS, including race, Hispanic/Latino status, poverty status, disability status and unemployment. Each of these variables is linked to food insecurity in the prior research described in our introduction.

We then modeled county level food insecurity using two methods, as shown in Figure 1. For our first approach, we calibrated a fixed effects model with household level food insecurity as the dependent variable and other demographic factors as independent variables: percent unemployed, percent disabled, percent with household income less than 185 percent of the poverty line, percent black, and percent Hispanic.

The second approach, demographic metabolism, identifies of the structure of food insecurity across demographic subgroups (Lutz 2012). In this method, we analyzed food insecurity rates by racial subgroups stratified by age within the CPS data. For example, we identified rates of food insecurity for African-Americans in each five year age group: under 4 years of age, 5-9 years of age, and so on.

These rates can then be applied to other datasets, such as tract level census data, to produce population estimates. Using additional subgroups beyond race is problematic, as the census does not offer age stratified cross tabulated data including all variables used in our fixed effects model. As a result, we used only race as a demographic variable with this method. This approach is justified as race has been a consistent predictor of food insecurity in past research (Gundersen et al. 2014).

Creating tract level estimates

To create census tract level estimates in phase two of our analysis, we made use of demographic data from both the American Community Survey (ACS) and the decennial census. For estimates of *current* food insecurity, we use ACS data at the tract level from 2009-2013 for the same variables as our fixed effects model above: rates of unemployment, disability status, and household income below 185 percent of the poverty line, as well as portions of the population classified as African-American and Hispanic.

For estimates of *future* food insecurity, we drew upon tract level decennial census data from 2000 and 2010, using the commonly employed Hamilton-Perry method with these data to create population estimates for 2020 (Swanson, Schlottmann, and Schmidt 2010). The Hamilton-Perry method utilizes cohort-change ratios (CCRs), computed from two censuses, to project populations by age and sex in a two-step process (Swanson, Schlottmann, and Schmidt 2010). The methods uses these two equations :

$${}_nCCR_x = \left(\frac{{}_nP_{x+y,l}}{{}_nP_{x,b}}\right)$$

$${}_nP_{x,t} = {}_nCCR_x * {}_nP_{x+y,l}$$

Where:

${}_{n}P_{x+y,l}$ is the population aged x to x+n at time *l*, the most recent census where *y* is the number of years between censuses.

${}_{n}P_{x,b}$ is the population aged x to x+n at time *b*, the second most recent census.

${}_{n}CCR_{x}$ is the cohort change ratio between time *b* and time *l*.

${}_{n}P_{x,t}$ is the population aged x to x+n at time *t*, the projected year

Hamilton-Perry requires two exceptions for the CCRs to accommodate births and the open-ended age interval of 85+. For births, the child/woman ratio for the populations aged 0-4 and 5-9 are calculated based on the number of women aged 15-45 and multiplied by the projected female population. For the open ended interval, the CCR is calculated as the ratio of the population aged 85+ to the population aged 75+. The result of Hamilton-Perry is complete age/sex projections for the population aged 0-75+ for each of our demographic subgroups.

We used these current and estimated populations to create our tract level estimates by applying the results produced by our county analyses using CPS data in phase one. In the fixed effects model approach, we applied model coefficients from the CPS data to the same variables 2009-2013 ACS and projected 2020 populations. For demographic metabolism, we applied food insecurity rates for each age stratified racial group groups in the current and projected tract level data. For example, if the food insecurity rate for African-Americans aged 40-44 was 14 percent in the CPS data, we would apply this rate to the same racial/age group in current tract level ACS data and to the group's projected population in 2020. We then summed the number of food insecure individuals in each subgroup within each tract to calculate the projected food insecurity rate.

Identifying clusters and trends

Our analysis of these tract level estimates identifies both the prevalence of food insecurity in current data and projected changes in 2020. We use local identifiers of spatial autocorrelation (LISA) analysis to identify statistically significant clusters in both cases. (Anselin 1995). LISA identifies regions where tracts and their neighbors are higher or lower than would be likely by chance or where a tract is a spatial outlier among its neighbors—a high value surrounded by low values, for example. In addition, to analyze regional trends, we visualize projected tract level change by county to identify those sections of the MSA containing tracts with particularly high or low change in rates. Lastly, we compare tracts with significant increases and decreases in food security to existing public transit infrastructure and food pantry locations to identify those areas where problems linked to spatial mismatch may increase in coming years.

Results

The results of our fixed effects model based on CPS county level data show that increases in rates of poverty, percentage African-American, and percentage unemployed were significantly associated with elevated rates of food insecurity (Table 1). Of these, the effect of unemployment had the greatest magnitude, roughly double that of increases in poverty or African-Americans (0.475 vs. 0.235 and 0.215 respectively). All listed coefficients were positive except for percent Hispanic/Latino, which showed a small negative effect. Though not significant, this result runs counter to other research showing elevated rates of food insecurity among Hispanic households

(Coleman-Jensen et al. 2014; Coleman-Jensen 2012). We include it in our model based on its significant role in prior research, but given the modest rate of Hispanics in the Atlanta MSA (10.4 percent in 2014 (U.S. Census Bureau 2015)) and the small coefficient, this variable has a minimal effect in our tract level estimates.

Table 1: Results for fixed effects regression of county level factors on food insecurity, based on yearly CPS data, 2009-2013

Variable	**Coefficient (SE)**
Percent in poverty	0.235*** (0.050)
Percent with a disability	0.152 (0.124)
Percent African-American	0.215** (0.078)
Percent Hispanic/Latino	-0.114 (0.093)
Percent unemployed	0.475** (0.173)

We use these coefficients to calculate tract level food insecurity based on American Community Survey data (figure 2B). Figure 2 shows these results (2B) alongside county level estimates from prior research (Gundersen et al. 2014) (2A), tract level estimates using demographic metabolism as a method (2C), and a comparison of these models (2D). A visual comparison demonstrates the advantage of tract estimation over county estimation. Tract level data highlight a division in Fulton and DeKalb counties, with low rates of food security in northern tracts and high rates in southern ones. In county level data, these two halves of the county counterbalance one another, producing a picture of moderate, but not extreme, food insecurity that obscures neighborhood level variation. In addition, tract level data also show a region with very high food insecurity rates that spans Fulton, DeKalb, and Clayton counties, a pattern likewise masked by county level data. Tract level data also reveal sub-county pockets of high food insecurity. Coweta, Walton and Cobb counties all appear to have low rates in figure 2A, but figures 3B and 3C show small areas of high food insecurity at the sub-county level.

While our two estimation methods produce geographically similar results, there are also notable differences (figure 2D). The fixed effects model has a higher mean food insecurity rate (19.5 percent vs. 17.4 percent) and also a higher standard deviation (9.5 percent vs. 5.5 percent). The fixed effects model is lower than demographic metabolism estimates in areas where food insecurity is low (the northern metro) and higher where food insecurity is high (southern Fulton, southern DeKalb, and Clayton counties), meaning that the fixed effects model produced greater variability in rates.

Figure 2: Comparison of two tract level food insecurity estimates and county level estimates from Gundersen, et al. (2014)

[Figure 2 about here]

Differences between our two methods are less apparent when calculating changes in food security from current to projected rates. According to the fixed effects model food insecurity will increase by an average of 0.12 percent (s.d. 1.19), while the demographic metabolism method predicts an average decrease of 0.08 percent (s.d. 1.27). Both these figures are close to zero, suggesting no significant change in the region as a whole. But some significant tract level trends are evident within the study area. Figure 3 depicts projected change in food insecurity rate at the tract level using both methods (3A and 3B), as well as clusters of high and low change levels across the study area as revealed by LISA analysis (3C and 3D). In both models, food insecurity rates are projected to increase in suburban tracts, especially in a band stretching from eastern Gwinnett County through Henry County. A less clearly defined band of increased rates is seen on the west side of the MSA in and around Paulding County. Rates are projected to decrease in the urban core in the middle sections of Fulton and DeKalb counties, though overall food insecurity will remain high in both these areas.

Figure 3: Change in food insecurity from present day to 2020 with clustering identified using LISA

[Fig. 3 about here]

To further illustrate this trend, figure 4 is a density plot showing the distribution of projected tract level changes in food insecurity aggregated by county. Several suburban counties, including Douglas, Henry, Newton, Paulding, and Rockdale, have centers skewed noticeably to the right of other counties, showing higher projected increases in food insecurity within their tracts. Other suburban counties show a bimodal distribution or positive skew, such as Fayette, Forsyth, and Gwinnett, suggesting divergent trends across tracts. Both the fixed effects model and demographic metabolism show similar trends.

Figure 4: Density plots of tract level change in food insecurity, current to 2020, aggregated by county

[Figure 4 about here]

Lastly, we examined the location of public transit routes and existing food pantry sites relative to areas where food insecure populations are expected to increase. In figure 5, the red lines are transit routes (5A) and red dots are food pantries (5B), while each black dot represents a projected 250 additional food insecure individuals by 2020. Both figures illustrate that the significant increase in food insecure populations in suburban areas sharply contrasts with the high density of both transit and pantries in the urban core. Some suburban areas with large increases in food insecure population have no access to transit and only limited access to food pantries. This includes several counties in the eastern suburbs (e.g. Henry and Newton counties), and southwest (southern Fulton County), and west (e.g. Paulding County). For Gwinnett County, in the northeast corner of the study area, several food pantries are already operating, but the significant projected increase of food insecurity in this area may overwhelm the current capacity of these sites.

Figure 5: Comparison of newly food insecure populations and existing public transit and food pantries

[Figure 5 about here]

Discussion

This analysis produced estimates of food insecurity at the census tract level for the Atlanta MSA. We know of no other research which has done so for an entire metropolitan area through use of publically available, annually produced secondary datasets. We used two different approaches to create our estimates, and while the fixed effects models produced estimates with more variability than demographic metabolism, both showed similar patterns of current and projected food insecurity across the MSA.

Currently, we find the highest rates of food insecurity in the southern half of the study area, particularly in Fulton, DeKalb, and Clayton counties, with pockets of high food insecurity scattered in the outer suburbs. Several of these within-county suburban clusters (e.g. Walton or Coweta counties), are obscured by county scale analysis. Our projections for 2020 show rates of food insecurity declining in the urban core and increasing in the suburbs, particularly in the eastern half of the MSA. The ability to forecast future trends, rather than retrospectively analyze survey data, is a significant benefit of our approach.

These findings correspond with broader research demonstrating that for many U.S. cities, poverty and its related effects are increasingly suburban problems (Anacker 2015; Kneebone and Garr 2010). Continued high rates of food insecurity in core urban neighborhoods demonstrate that anti-hunger efforts there should continue, but attention should also be given to the increasing challenges facing food insecure households in suburban areas. For example, Atlanta has one of the highest rates of urban sprawl of any American city, necessitating high rates of auto use and relatively poor access to public transit, as Figure 5 illustrates (Basmajian 2013; Brown and Thompson 2008; Bullard, Johnson, and Torres 2000). The expansion of public transit in Atlanta remains a politically charged issue but has serious consequences for the growing number of food insecure households in suburban areas that lack access to resources such as food pantries in their immediate neighborhoods (Bluestein 2016).

The task for hunger assistance programs, then, is not just how to provide access to food through food pantries or monetary assistance, but also how to help households navigate sprawling suburban landscapes or increasing use of projects such as mobile food pantries. Additionally, anti-hunger efforts in suburban communities may necessitate different forms of mobilization than in the urban core, including informational campaigns about increased food insecurity for residents and community leaders, advocacy for transit expansion and improved service sector wages, support for community agriculture, and innovative methods for delivering health care and related social services (Bastian and Napieralski 2015). Specific strategies may include placing mobile food pantries at sites already part of daily routines (e.g., schools or transit centers). For example, the Atlanta Community Food Bank—who provided a grant for this research—partners with Covington First United Methodist on a mobile pantry program. This initiative takes place in one of our projected hot spots for growth in food insecurity, and it delivers up to 15,000 pounds of food, or enough for 200-250 families each month as a supplement to weekly pantry food distribution.

“One stop shop” sites that combine medical care, food assistance, and job counseling also help lower the time and financial costs of seeking assistance, particularly in suburban communities where these costs can be high. In Atlanta for example, the Community Assistance Center in suburban Sandy Springs provides adult classes, tax preparation, financial assistance, and help with enrolling for government assistance programs such as SNAP or SSI (Community Assistance Center 2017). Informational campaigns designed to dispel the stigma associated with food insecurity and can also highlight the challenges of low wage employment in suburban communities. These approaches recognize the need for a relational approach to food insecurity and similar health concerns, adopting a holistic perspective on the processes that produce and reproduce health disparities (Cummins et al. 2007; Sonnino, Marsden, and Moragues-Faus 2016).

Our study has several limitations. We conduct our analysis on just one major American city, and a similar analysis may find different patterns in other metropolitan areas. Still, one main benefit our approach is the relative ease with which it can be duplicated. Because our analysis included population projections, we were limited to only variables with detailed age stratification available. For example, we were not able to include variables such as home ownership, where the Census provides only broad age breakdowns (e.g., age 18-64). Finally, as our estimates are derived from Census data, they do not fully replace survey based approaches that may result in more accurate figures.

In spite of these limitations, this analysis provides insight into changing patterns of food insecurity at the neighborhood level within a major American city using publicly available data. It demonstrates that food insecurity is a growing issue in suburban communities as well as in core urban areas. Addressing the challenges of sprawl and spatial mismatch may thus be key challenges in anti-hunger work and activism in future years.

References

Allard, S. W. (2009). *Out of reach : place, poverty, and the new American welfare state*. New Haven: Yale University Press.

Anacker, K. B. (Ed.). (2015). *The New American Suburb: Poverty, Race and the Economic Crisis*. New York: Routledge.

Anselin, L. (1995). Local Indicators of Spatial Association-LISA. *Geographical Analysis*, *27*(2), 93–115.

Bartfeld, J., and Dunifon, R. (2007). State-Level Predictors of Food Insecurity among Households with Children. *Journal of Policy Analysis and Management*, *25*(4), 921–942. doi:10.1002/pam.20214

Basmajian, C. W. (2013). *Atlanta unbound : enabling sprawl through policy and planning*. Philadelphia: Temple Univ. Press.

Bastian, Elizabeth, and Jacob Napieralski. 2015. "Suburban Food Security: Walkability and Nutritional Access in Metropolitan Detroit." *The Professional Geographer* 68(3):462–74.

Bluestein, G. (2016). Atlanta can now pursue a $2.5B MARTA transit expansion. *Atlanta Journal Constitution*. Retrieved from http://politics.blog.ajc.com/2016/04/26/atlanta-can-now-pursue-a-2-5b-marta-transit-expansion (last accessed 13 August 2016).

Blumenberg, E. (2004). En-gendering Effective Planning: Spatial Mismatch, Low-Income Women, and Transportation Policy. *Journal of the American Planning Association*, *70*(3), 269–281. doi:10.1080/01944360408976378

Brown, J. R., and Thompson, G. L. (2008). The relationship between transit ridership and urban decentralisation: Insights from Atlanta. *Urban Studies*, *45*(5-6), 1119–1139. doi:10.1177/0042098008089856

Bullard, R. D., Johnson, G. S., and Torres, A. O. (Eds.). (2000). *Sprawl City: Race, Politics, and Planning in Atlanta*. Washington D.C.: Island Press.

Carter, M. A., Dubois, L., and Tremblay, M. S. (2014). Place and food insecurity: a critical review and synthesis of the literature. *Public Health Nutrition*, *17*(1), 94–112. doi:10.1017/S1368980013000633

Chung, W. T., Gallo, W. T., Giunta, N., Canavan, M. E., Parikh, N. S., and Fahs, M. C. (2012). Linking neighborhood characteristics to food insecurity in older adults: the role of perceived safety, social cohesion, and walkability. *Journal of Urban Health*, *89*(3), 407–18. doi:10.1007/s11524-011-9633-y

Coleman-Jensen, A. (2012). Predictors of U.S. Food Insecurity Across Nonmetropolitan, Suburban, and Principal City Residence During the Great Recession. *Journal of Poverty*, *16*(4), 392–411. doi:10.1080/10875549.2012.720657

Coleman-Jensen, A., Gregory, C., and Singh, A. (2014). *Household food security in the United States in 2013*. Retrieved from http://www.ers.usda.gov/publications/err-economic-research-report/err173.aspx (last accessed 3 June 2016).

Coleman-Jensen, A., Nord, M., Andrews, M., and Carlson, S. (2011). *Household Food Security in the United States in 2010*. Retrieved from http://www.ers.usda.gov/webdocs/publications/err125/6891_err125_reportsummary.pdf (last accessed 24 July 2016).

Coleman-Jensen, A., Rabbitt, M. P., Gregory, C., and Singh, A. (2015). *Household Food Security in the United States in 2014*. Retrieved from http://www.ers.usda.gov/media/1896841/err194.pdf

Cooper, H. L. F., Wodarski, S., Cummings, J., Hunter-Jones, J., Karnes, C., Ross, Z., … Bonney, L. E. (2012). Public housing relocations in Atlanta, Georgia, and declines in spatial access to safety net primary care. *Health and Place*, *18*(6), 1255–60. doi:10.1016/j.healthplace.2012.08.007

Community Assistance Center. (2017). *Community Assistance Center.* http://www.ourcac.org/services-financial (last accessed 4 March 2017).

Cummins, S., Curtis, S., Diez-Roux, A. V, and Macintyre, S. (2007). Understanding and representing “place” in health research: A relational approach. *Social Science and Medicine*, *65*(9), 1825–1838. doi:10.1016/j.socscimed.2007.05.036

Gundersen, C., Engelhard, E., and Waxman, E. (2014). Map the Meal Gap: Exploring Food Insecurity at the Local Level. *Applied Economic Perspectives and Policy*, *36*(3), 373–386. doi:10.1093/aepp/ppu018

Gundersen, C., Kreider, B., and Pepper, J. (2011). The Economics of Food Insecurity in the United States. *Applied Economic Perspectives and Policy*, *33*(3), 281–303. doi:10.1093/aepp/ppr022

Harris, D. E., Aboueissa, A.-M., Walter, K., and Bampton, M. (2014). Predictors of Food Insecurity in Lewiston, Maine: A Community-Level Analysis. *Journal of Hunger and Environmental Nutrition*, *9*(1), 96–112. doi:10.1080/19320248.2013.840549

Heflin, C. M., Siefert, K., and Williams, D. R. (2005). Food insufficiency and women’s mental health: Findings from a 3-year panel of welfare recipients. *Social Science and Medicine*, *61*(9), 1971–1982. doi:10.1016/j.socscimed.2005.04.014

Holloway, S. R., Wright, R., and Ellis, M. (2012). The Racially Fragmented City? Neighborhood Racial Segregation and Diversity Jointly Considered. *The Professional Geographer*, *64*(1), 63–82. doi:10.1080/00330124.2011.585080

Jarosz, L. (2014). Comparing food security and food sovereignty discourses. *Dialogues in Human Geography*, *4*(2), 168–181. https://doi.org/10.1177/2043820614537161

Kalichman, S. C., Cherry, C., Amaral, C., White, D., Kalichman, M. O., Pope, H., Macy, R. (2010). Health and treatment implications of food insufficiency among people living with HIV/AIDS, Atlanta, Georgia. *Journal of Urban Health*, *87*(4), 631–641. doi:10.1007/s11524-010-9446-4

Kirkpatrick, S. I., McIntyre, L., and Potestio, M. L. (2010). Child hunger and long-term adverse consequences for health. *Arch Pediatr Adolesc Med*, *164*(8), 754–762. doi:10.1001/archpediatrics.2010.117

Kneebone, E., and Berube, A. (2013). *Confronting suburban poverty in America*. Washington, D.C.: Brookings Institution Press.

Kneebone, E., and Garr, E. (2010). *The Suburbanization of Poverty: Trends in Metropolitan America, 2000 to 2008.* Retrieved from http://www.brookings.edu/research/papers/2010/01/20-poverty-kneebone (last accessed 2 February 2016).

Laraia, B. A. (2012). Food Insecurity and Chronic Disease. *Advances in Nutrition*, *4*, 203–212. doi:10.3945/an.112.003277.Current

Lassiter, M. D., and Niedt, C. (2013). Suburban Diversity in Postwar America. *Journal of Urban History*, *39*(1), 3–14. doi:10.1177/0096144212463541

Lee, J. S., Shannon, J., and Brown, A. (2014). Living in food deserts was associated with food insecurity in a statewide sample of older adults in need of aging and food assistance programs in Georgia. *Journal of the Academy of Nutrition and Dietetics*, *114*(9), A12.

Leung, C. W., Epel, E. S., Ritchie, L. D., Crawford, P. B., and Laraia, B. A. (2014). Food Insecurity Is Inversely Associated with Diet Quality of Lower-Income Adults. *Journal of the Academy of Nutrition and Dietetics*, *114*(12), 1943–1953. doi:10.1016/j.jand.2014.06.353

Li, H., Campbell, H., and Fernandez, S. (2013). Residential Segregation, Spatial Mismatch and Economic Growth across US Metropolitan Areas. *Urban Studies*, *50*(13), 2642–2660.

doi:10.1177/0042098013477697

Lutz, W. (2012). Demographic Metabolism: A theory of Socioeconomic Change with Predictive Power. *Population and Development Review*, *38*, 283–301.

Mayer, V. L., Hillier, A., Bachhuber, M. a, and Long, J. a. (2014). Food insecurity, neighborhood food access, and food assistance in Philadelphia. *Journal of Urban Health*, *91*(6), 1087–97. doi:10.1007/s11524-014-9887-2

Pooley, K. B. (2015). Debunking the "Cookie-Cutter" Myth for Suburban Places and Suburban Povetry: Analyzing Their Variety and Recent Trends. In K. B. Anacker (Ed.), *The New American Suburb: Poverty, Race and the Economic Crisis* (pp. 39–80). New York: Routledge.

Research Triangle Institute. (2014). *Current and Prospective Scope of Hunger and Food Security in America: A Review of Current Research*. Retrieved from http://www.rti.org/pubs/full_hunger_report_final_07-24-14.pdf (last accessed 23 August 2016).

Sattler, E. L. P., and Lee, J. S. (2013). Persistent food insecurity is associated with higher levels of cost-related medication nonadherence in low-income older adults. *Journal of Nutrition in Gerontology and Geriatrics*, *32*(1), 41–58. doi:10.1080/21551197.2012.722888

Seligman, H., Laraia, B., and Kushel, M. (2010). Food insecurity is associated with chronic disease among low-income NHANES participants. *The Journal of Nutrition*, *140*, 304–310. doi:10.3945/jn.109.112573.number

Slopen, N., Fitzmaurice, G., Williams, D. R., and Gilman, S. E. (2010). Poverty, food insecurity, and the behavior for childhood internalizing and externalizing disorders. *Journal of the American Academy of Child and Adolescent Psychiatry*, *49*(5), 444–452. doi:10.1016/j.jaac.2010.01.018

Sonnino, R., Marsden, T., and Moragues-Faus, A. (2016). Relationalities and convergences in food security narratives: towards a place-based approach. *Transactions of the Institute of British Geographers*. doi:10.1111/tran.12137

Swanson, D. A., Schlottmann, A., and Schmidt, B. (2010). Forecasting the population of census tracts by age and sex: An example of the Hamilton-Perry method in action. *Population Research and Policy Review*, *29*(1), 47–63. doi:10.1007/s11113-009-9144-7

U.S. Census Bureau. (2015). American FactFinder. Retrieved from http://factfinder2.census.gov (last accessed 15 October 2016).

------. (2016a). Cartographic Boundary Shapefiles - Metropolitan and Micropolitan Statistical Areas and Related Statistical Areas. Retrieved from https://www.census.gov/geo/maps-data/data/cbf/cbf_msa.html (last accessed 6 June 2016).

------. (2016b). Census Regions and Divisions of the United States. Retrieved from http://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf (last accessed 26 May 2016).

Acknowledgments

This research was supported by a grant from the Atlanta Community Food Bank.

Authors biographies

Jerry Shannon is an Assistant Professor in the Department of Geography and the Department of Financial Planning, Housing, and Consumer Economics at the University of Georgia. E-mail: jshannon@uga.edu. His research interests include food access and food security, neighborhood development, and community engaged research.

Mathew Hauer is an Applied Demographer at the Carl Vinson Institute of Government at the

University of Georgia. E-mail: hauer@uga.edu. His research interests include small area demographic projections, population geography, and climate change.

Alexis Weaver is Community Impact Manager for the Atlanta Community Food Bank. E-mail: alexis.weaver@acfb.org . She currently manages the Food Bank's strategic initiative to understand the relationship between food security and household economic stability and the food pantry's role in that relationship.

Sarah Shannon is an assistant professor of sociology at the University of Georgia. E-mail: sshannon@uga.edu. She studies law, crime, and deviance, with a focus on how social institutions like the criminal justice and public welfare systems affect social inequality.