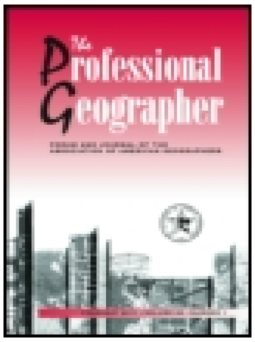

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The Suburbanization of Food Insecurity: An Analysis of Projected Trends in the Atlanta Metropolitan Area

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Although general patterns of food insecurity in the United States 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 to 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 that 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 antihunger efforts for often sprawling suburban communities, where poverty rates are increasing but spatial mismatch combined with poor transit access might hinder access to food assistance. **Key Words: Atlanta, food insecurity, spatial mismatch, suburbanization of poverty.**

尽管美国粮食不安全的一般模式已为人所知，但却鲜少有研究尝试评估小面积的粮食不安全，抑或考量持续进行的社会经济变迁。我们于此运用固定效应模式化与人口新陈代谢两大方法，藉由生产亚特兰大大都会地区的小面积粮食不安全评估，应对上述议题。我们同时在两个案例中， 运用当前人口调查中的郡县层级数据， 决定粮食不安全与人口预测指标之间的关联性。这些关联性接着应用至美国社区调查 2009 年至 2013 年人口普查区块层级的数据，以及 2020 年的预测数据，以创造粮食不安全的小面积评估。我们发现这两个方法之间的广泛共识。在两个时期中， 粮食不安全在亚特兰大市的南部区段及其周边的郊区中最高。但 2020 年的预测却显示，粮食不安全率在城市东边与南边的郊区外缘将有所增加，而城市中心则将降低。这些结果凸显出必须为经常蔓延的郊区社区进一步调适抵抗飢饿的努力。这些地方的贫穷率将逐渐增加， 但空间不协调与贫乏的交通管道结合之下，将可能妨碍取得粮食的协助。 **关键词：亚特兰大，粮食不安全，空间不协调，贫穷的郊区化。**

Aunque se conocen los patrones generales de la inseguridad alimentaria en los Estados Unidos, pocos estudios han intentado calcular la seguridad alimentaria de áreas pequeñas o relacionarlas con los cambios socioeconómicos en curso. En este trabajo nosotros abocamos estas cuestiones produciendo estimativos de inseguridad alimentaria de área pequeña en el área metropolitana de Atlanta, usando dos metodologías: modelado de efectos fijos y metabolismo demográfico. En ambos casos, usamos datos a nivel de condado del Estudio de la Población Actual [Current Popultion Survey] para determinar la asociación entre inseguridad alimentaria e indicadores demográficos. Posteriormente, estas asociaciones se aplican a datos del Estudio de la Comunidad Americana a nivel de tracto censal de 2009 a 2013, y a datos proyectados para 2020 para crear estimativos de inseguridad alimentaria de área pequeña. Hallamos amplio consenso entre nuestros dos métodos. Para ambos períodos de tiempo, la inseguridad alimentaria se registra al máximo en las secciones sureñas de la ciudad de Atlanta y sus suburbios vecinos. Sin embargo, las proyecciones para el 2020 muestran que las tasas de inseguridad alimentaria se proyectan incrementadas en los suburbios del anillo externo, al este y oeste de la ciudad, mientras se proyectan decrecientes en el núcleo urbano. Estos resultados resaltan la necesidad de adaptar más los esfuerzos contra el hambre para las comunidades suburbanas propensas a expandirse, donde las tasas de pobreza están aumentando, pero la discordancia espacial combinada con deficiente acceso al tránsito podría obstaculizar el acceso a la ayuda alimentaria. **Palabras clave: Atlanta, inseguridad alimentaria, discordancia espacial, suburbanización de la pobreza.**

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 et al. 2015)—plays a foundational role in households' health and welfare. Recent research finds that low food security—or food *insecurity*—is correlated with depression

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and developmental disorders (Heflin, Siefert, and Williams 2005; Kirkpatrick, McIntyre, and Potestio 2010; Slopen et al. 2010; Carter, Dubois, and Tremblay 2014), poorer nutritional intake (Leung et al. 2014), weight gain, and other chronic diseases (Seligman, Laraia, and Kushel 2010; Laraia 2012). Although 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 (Jarosz 2014; Sonnino, Marsden, and Moragues-Faus 2016). 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) identified 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 nonprofit 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 that the most rapid increases in poverty—closely correlated with food insecurity—have occurred in suburban neighborhoods (Kneebone and Garr 2010; Kneebone and Berube 2013; Anacker 2015). 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). Although 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 United States 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 (Blumenberg 2004; Allard 2009; 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 might 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 (Kalichman et al. 2010; Chung et al. 2012; Harris et al. 2014; Lee, Shannon, and Brown 2014; Mayer et al. 2014). Although 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 (Lutz 2012; Gundersen, Engelhard, and Waxman 2014). We show how existing infrastructure related to public transit and available food assistance might 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 U.S. cities and informs future planning efforts for local antihunger 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, Kreider, and Pepper (2011), we first employ fixed effects modeling to identify relationships between food insecurity and several demographic variables using existing county-level data from the CPS. We then apply the coefficients from these models to existing tract-level data from the ACS (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

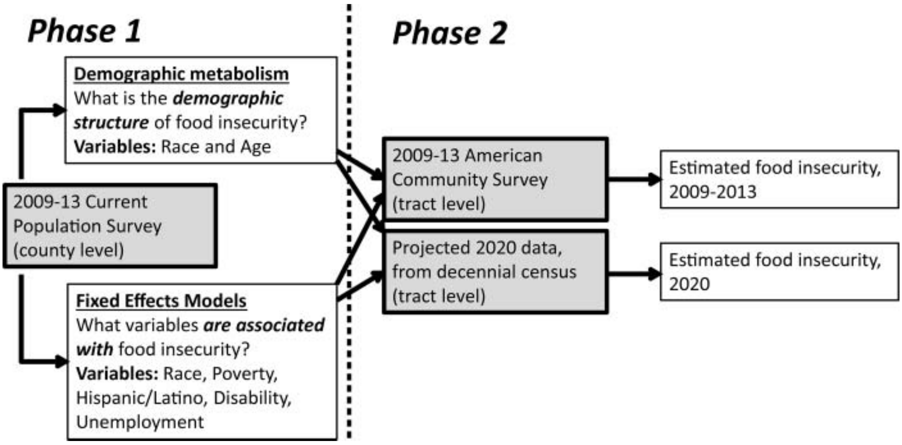

Figure 1 *Outline of process used for tract estimation.*

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 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.

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, making it the ninth largest in the country (U.S. 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 nonwhite residents than the country as a whole. Whereas 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 1 of our analysis, we use publicly 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 eighty-one counties was reduced to sixty-nine 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' abilities 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 (Sattler and Lee 2013; Coleman-Jensen, Gregory, and Singh 2014). 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 or 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: percentage unemployed, percentage disabled, percentage with household income less than 185 percentage of the poverty line, percentage black, and percentage Hispanic.

The second approach, demographic metabolism, identifies 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 four years of age, five to nine years of age, and so on. These rates can then be applied to other data sets, 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, Engelhard, and Waxman 2014).

Creating Tract-Level Estimates

To create census tract–level estimates in Phase 2 of our analysis, we made use of demographic data from both the ACS and the decennial census. For estimates of *current* food insecurity, we use ACS data at the tract level from 2009 to 2013 for the same variables as our fixed effects model earlier: 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 on 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 method uses these two equations:

$$_{n}CCR_{x} = \left(\frac{_{n}P_{x+y,l}}{_{n}P_{x,b}}\right)$$

$$_{n}P_{x,t} = {}_{n}CCR_{x} * {}_{n}P_{x+y,l},$$

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; and $_{n}P_{x,t}$ 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 eighty-five and older. For births, the child–woman ratios for the populations aged zero to four and five to nine are calculated based on the number of women aged fifteen to forty-five and multiplied by the projected female population. For the open-ended interval, the CCR is calculated as the ratio of the population aged eighty-five and older to the population aged seventy-five and older. The result of Hamilton–Perry is complete age and sex projections for the population aged zero to seventy-five and older 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 1. In the fixed effects model approach, we applied model coefficients from the CPS data to the same variables for the 2009–2013 ACS and projected 2020 populations. For demographic metabolism, we applied food insecurity rates for each age-stratified racial group in the current and projected tract-level data. For example, if the food insecurity rate for African Americans aged forty to forty-four was 14 percent in the CPS data, we would apply this rate to the same racial and 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 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

Table 1 *Results for fixed effects regression of county-level factors on food insecurity, based on yearly Current Population Survey data, 2009–2013*

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

$*p < 0.01$; $**p < 0.005$.

particularly high or low change in rates. Finally, 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 might 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 percentage Hispanic or Latino, which showed a small negative effect. Although not significant, this result runs counter to other research showing elevated rates of food insecurity among Hispanic households (Coleman-Jensen 2012; Coleman-Jensen, Gregory, and Singh 2014). 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.

We use these coefficients to calculate tract-level food insecurity based on ACS data (Figure 2B). Figure 2A shows these results alongside county-level estimates from prior research (Gundersen, Engelhard, and Waxman 2014), Figure 2C shows tract-level estimates using demographic metabolism as a method, and Figure 2D shows a comparison of these models. 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 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 subcounty pockets of high food insecurity. Coweta, Walton, and Cobb counties all appear to have low rates in Figure 2A, but Figures 2B and 2C show small areas of high food insecurity at the subcounty level.

Although 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.

Differences between our two methods are less apparent when calculating changes in food security

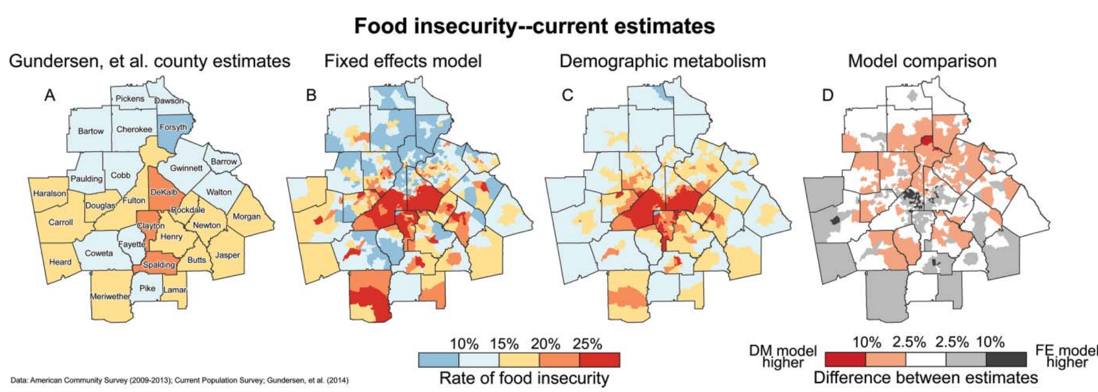

Figure 2 *Comparison of two tract-level food insecurity estimates and county-level estimates from Gundersen, Engelhard, and Waxman (2014). DM = demographic metabolism; FE = fixed effects. (Color figure available online.)*

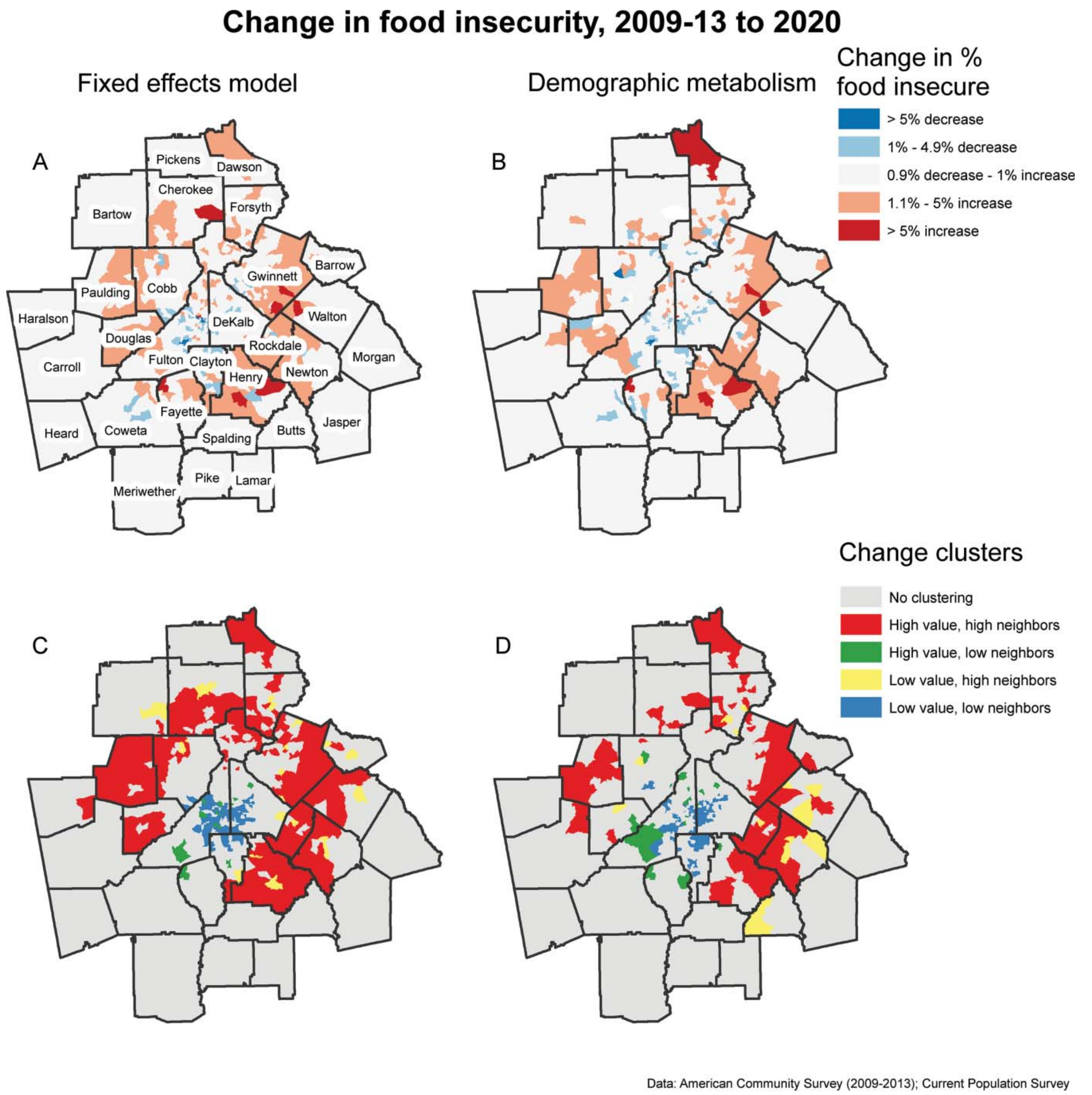

Figure 3 *Change in food insecurity from present day to 2020 with clustering identified using local indicators of spatial association. (Color figure available online.)*

from current to projected rates. According to the fixed effects model, food insecurity will increase by an average of 0.12 percent (SD = 1.19), whereas the demographic metabolism method predicts an average decrease of 0.08 percent (SD = 1.27). Both of these figures are close to zero, suggesting no significant change in the region as a whole. Some significant tract-level trends are evident within the study area, though. Figure 3 depicts projected change in food insecurity rate at the tract level using both methods (Figures 3A and 3B), as well as clusters of high and low change levels across the study area as revealed by LISA analysis (Figures 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 of these areas.

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.

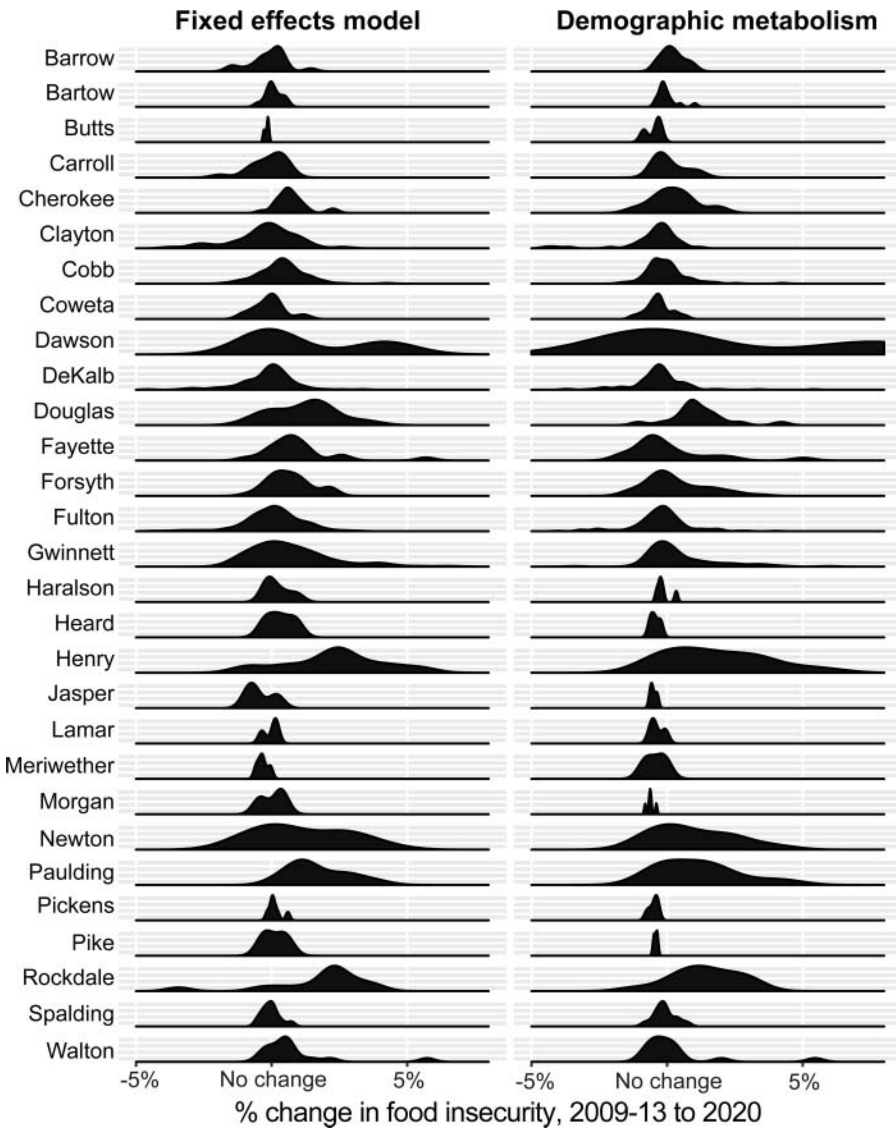

Figure 4 *Density plots of tract-level change in food insecurity, current to 2020, aggregated by county.*

Finally, 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 (Figure 5A) and red dots are food pantries (Figure 5B); 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 the 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), 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 might overwhelm the current capacity of these sites.

Discussion

This analysis produced estimates of food insecurity at the census tract level for the Atlanta MSA. We know of no other research that has done so for an entire metropolitan area through use of publicly available, annually produced secondary data sets. We used two different approaches to create our estimates, and though the fixed effects models produced estimates

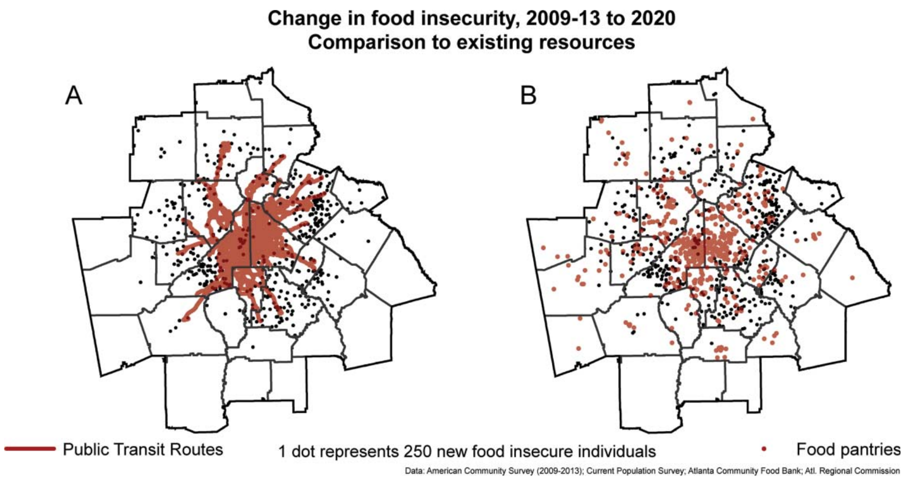

Figure 5 *Comparison of newly food insecure populations and existing public transit and food pantries. (Color figure available online.)*

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 County), 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 (Kneebone and Garr 2010; Anacker 2015). Continued high rates of food insecurity in core urban neighborhoods demonstrate that antihunger 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 U.S. city, necessitating high rates of auto use and relatively poor access to public transit, as Figure 5 illustrates (Bullard, Johnson, and Torres 2000; Brown and Thompson 2008; Basmajian 2013). 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 question 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, antihunger efforts in suburban communities might 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 might 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—which 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 to 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 the Supplemental Nutrition Assistance Program or Supplemental Security Income (Community Assistance Center 2017). Informational campaigns designed to dispel the stigma associated with food insecurity 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 conducted our analysis on just one major U.S. city, and a similar analysis might 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 homeownership, where the census provides only broad age breakdowns (e.g., age eighteen to sixty-four). Finally, as our estimates are derived from census data, they do not fully replace survey-based approaches that might result in more accurate figures.

Despite these limitations, this analysis provides insight into changing patterns of food insecurity at the neighborhood level within a major U.S. 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 could thus be key challenges in antihunger work and activism in future years. ■

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