Food Insecurity in 2020 for the Atlanta Community Food Bank Service Area

Completed for the Atlanta Community Food Bank
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Summary

- In this analysis, we developed two methods to estimate current and projected food insecurity at the tract level for the Atlanta Community Food Bank (ACFB) service area: a fixed effects model and demographic metabolism.
- These models show the highest rates of food insecurity in the southern Atlanta metropolitan area, specifically in southern Fulton and DeKalb counties and in Clayton County. Other pockets of food insecurity are also seen in suburban and a handful of non-metro counties.
- We project increasing rates of food insecurity will be concentrated in the outer Atlanta suburbs, particularly in eastern and southern parts of the city.
- Parts of central Atlanta will see slight declines in food insecurity, though large areas of high need will remain.

Data & Methods

To our knowledge, no studies have attempted to create fine scale projections of food security within the United States. Feeding America's national Map the Meal Gap study uses state level CPS data to create nation-wide county level estimates (Feeding America, 2012). First, this study calibrated a fixed effects model using existing CPS state level data. These authors then combined the coefficients from this model with county level demographics from the ACS to create state level estimates. Bartfeld and Dunifon (2007) use hierarchial linear models in a similar way, estimating county level food insecurity. More generally, a number of studies have identified demographic characteristics associated with food insecurity, such as race, unemployment, and poverty (Coleman-Jensen, Nord,& Singh, 2013; Harris, Aboueissa, Walter, & Bampton, 2014; Mayer, Hillier, Bachhuber, & Long,2014; Research Triangle Institute, 2014). There is, however, no widely available research that has estimated tract level food security at a regional scale.

Our estimates of food security came from two primary data sources. The Current Population Survey (CPS) is a monthly, national survey. Once each year, the CPS also includes the Food Security Supplement, a series of questions designed to assess households' ability to meet their basic dietary needs (Coleman-Jensen et al., 2013). 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. Based on individual responses, the USDA classifies respondents into one of four categories: high food security, marginal food security, low food security, and very low food security. While all four categories can be useful, it is common practice to group the latter two into a single category of food insecure (Coleman-Jensen et al., 2013; Sattler & Lee, 2013). For this project, we used this condensed classification as the variable of interest, along with other demographic variables provided by the CPS, including race, Hispanic/Latino status, poverty status, disability status and unemployment. After assessing models across a range of scales, we relied on publically available data for counties in the Southeast region, as defined by the U.S. Census.

Our second data source is the U.S. Census, both the American Community Survey (ACS) and the shorter decennial census. Beginning in 2005, the ACS replaced the Census long form. While both ask detailed questions on a variety of topics ranging from education to labor force participation, the long form was only administered in decennial years (e.g., 1980, 1990, 2000). The ACS is administered annually, though with a much smaller sample size. The results in greater temporal precision than the long form, but less geographic precision. For this study, we will be using ACS data at the tract level. To create these fine scale estimates, the Census pools samples together across five year windows. We used ACS data from the most recent available sample, 2009-2013, for the fixed effects model estimating tract level food security. We used

data from earlier samples to project values for our independent variables to 2020. Census data in 2010, which was also used for population projections, provides more accurate data for a small set of variables, most notably age and race.

Our work assesses the effectiveness of two different methodologies. The first is an adapted form of the fixed effects model used in Feeding America's research. Using yearly CPS data from 2009-2013 at the county level, 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% of the poverty line, percent black, and percent Hispanic. These variables were chosen based on a review of literature on food insecurity and its associated risk factors. Some variables are the same as the Map the Meal Gap study: poverty, unemployment, percent black, and percent unemployed. We have added percent disabled and also examined percent foreign born, though this was not significant and was dropped in our final model.

Using our fitted model, we then estimated current food insecurity at the census tract level using 2009-2013 ACS demographic information for the same independent variables. We projected total population in 2020 using data from the decennial census, and then estimated values for our independent variables based on the composition of this population. By using these new projected rates in our fixed effects model, we were able to estimate food insecurity for 2020 at the tract level.

The second method uses demographic metabolism, which uses current patterns of food insecurity to predict future rates (Lutz, 2012). In this method, we stratified rates of food insecurity by age and race. Rates of food insecurity are identified within these subgroups based on CPS data. We then applied these rates to the same subgroups in the current and 2020 population, based on ACS data, to create tract level estimates of food insecurity for both time frames.

Both of these methods produced current and projected food insecurity estimates. We visualized the resulting rates and the changes between time periods to identify regions where rates of food insecurity would increase through the study period. We also used local identifiers of spatial autocorrelation (LISA) analysis to identify statistically significant clusters in these changes.

Findings

Patterns of food insecurity across the study area

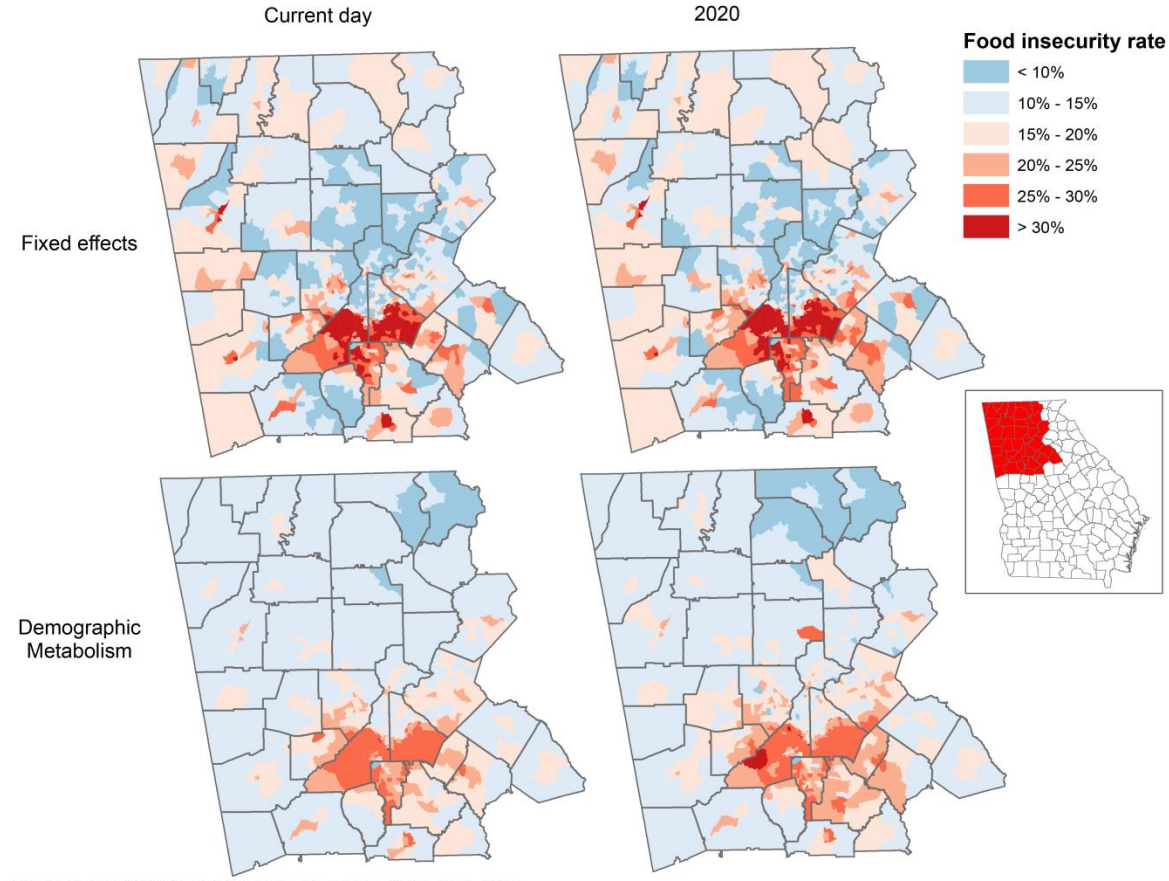
Figure 1 shows current and projected rates of food insecurity at the tract level for both the fixed effects and demographic metabolism methods for the ACFB service area. As this figure shows, there are much larger differences between these two methodologies than there are between their current and projected values. The fixed effects model shows a wider range of values across the study area, with higher rates of food insecurity both inside and outside of metro Atlanta. The demographic metabolism method had a lower maximum rate than the fixed effects model (32% vs. 52%), as a comparison of southern Fulton and DeKalb counties makes clear. Without ground truthing these estimates, there is no definitive way to assess which model provides the most valid estimate. Rather, the differences between these methods highlight that these are *estimated* tract level values, and that it is the pattern of these rates, rather than their exact values, that is most useful.

When looking at these patterns of high and low rates, these two models do share significant similarities. Figures 2 and 3 provide a closer look at projected 2020 food insecurity. Both see the largest concentration of high food insecurity rates in the southern half of metro Atlanta, particularly in southern Fulton and DeKalb counties as well as much of Clayton County. We see elevated rates of food insecurity in several other counties in the eastern metro area, including Henry, Rockdale, Newton, and Gwinnett, and in the

west, such as Douglas and Cobb counties. Some non-metro counties show pockets of food insecurity, such as Floyd, Dawson, and Hall counties.

The lowest rates of food insecurity are found in the north metro, including northern Fulton County as well as Cherokee and Forsyth Counties. Northeast Cobb County also has notably low rates. The two methods conflict on rates in the northeast portion of the study area, with the demographic metabolism approach showing low rates but the fixed effects model resulting in a mix of high and low values. This difference is one that would require more detailed local data collection to investigate.

Figure 1: Current and projected tract food insecurity, based on our two methodologies.



Data: CPS, ACS (2009-2013 data), Decennial census (1990, 2000, 2010)
Map by Community Mapping Lab, UGA Dept. of Geography
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Figure 2: Projected 2020 food insecurity rates using the fixed effects model

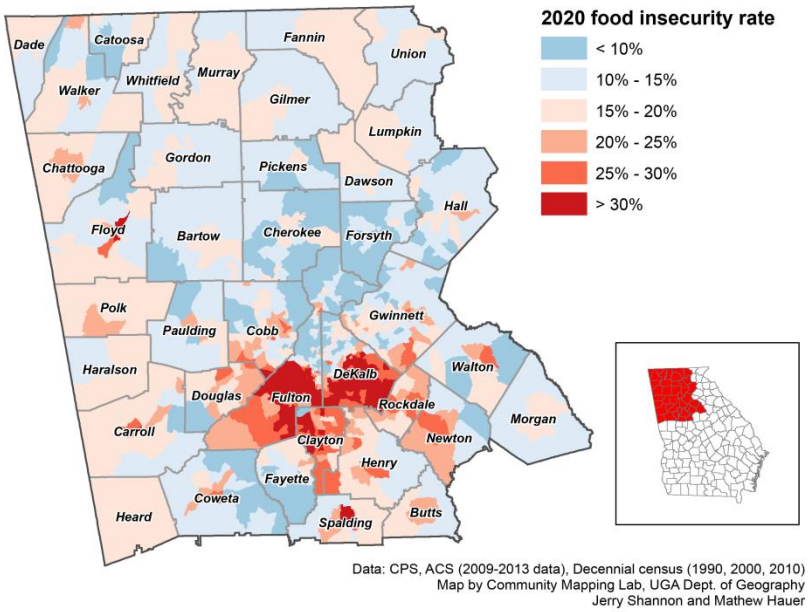
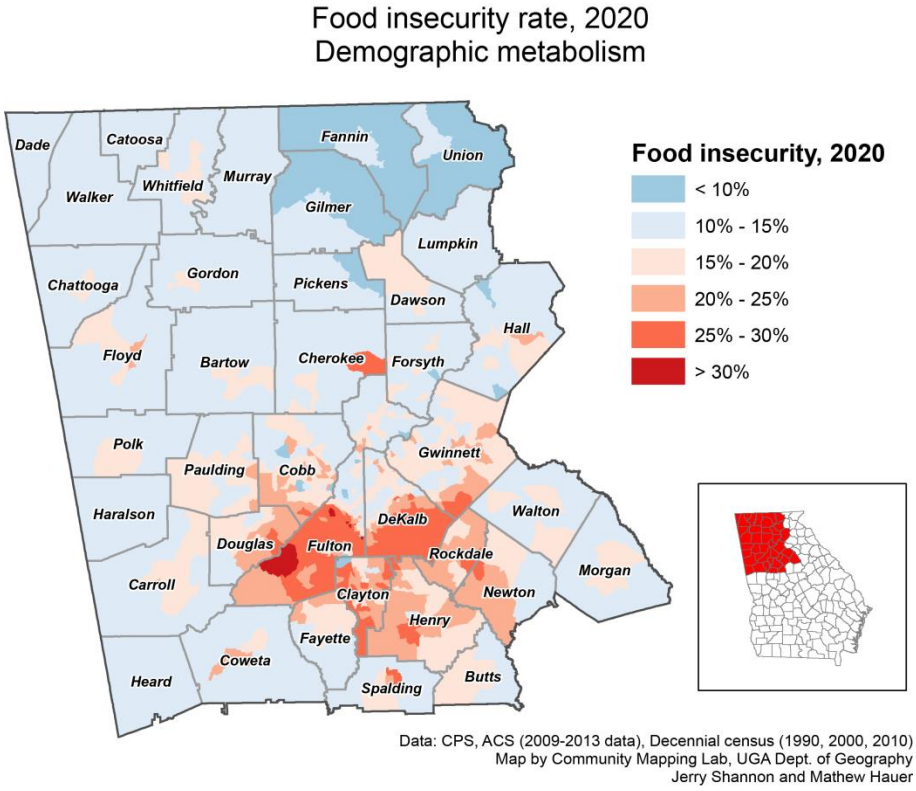


Figure 3: Projected 2020 food insecurity rates using the demographic metabolism method

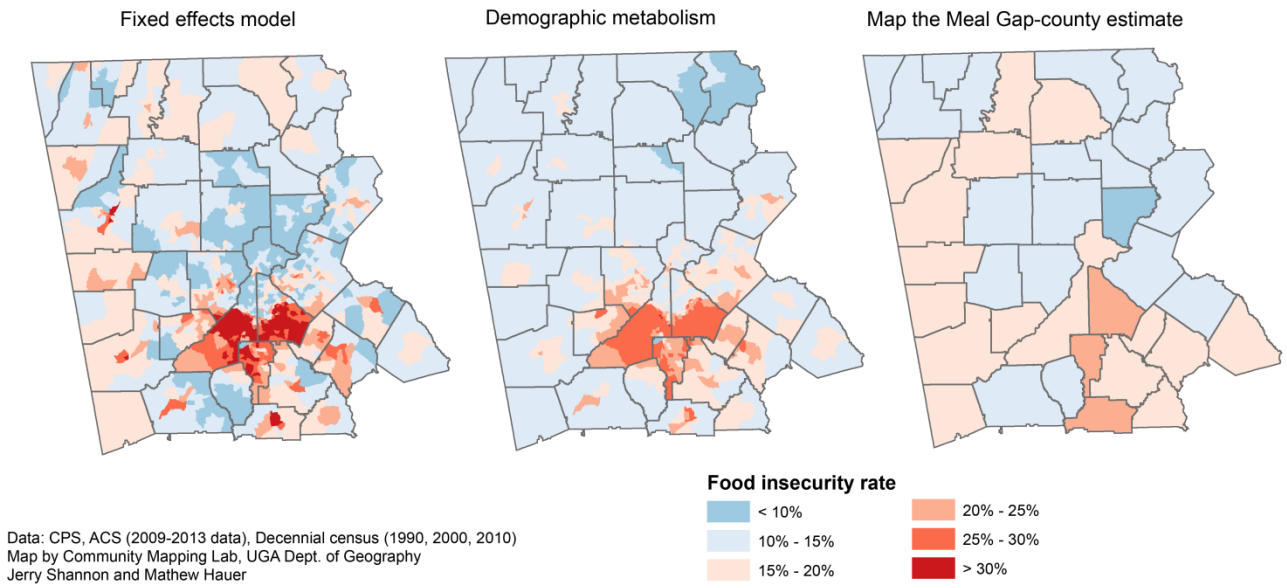


Comparison to national study

Figure 4 shows a comparison of these two methods against estimated county level food insecurity from Feeding America's Map the Meal Gap study. Two significant points stand out from this comparison. First,

the fixed effects model has a closer correspondence with estimates from Feeding America's study, particularly for rural counties on the western edge of the service area. Given that these two use very similar methodologies and data, this is unsurprising, but it does support the validity of tract level estimation. Second, these maps show evidence of the Modifiable Areal Unit Problem (MAUP), which is a common issue in spatial analysis. MAUP refers to the ways that analysis is affected by data aggregation. An example here is how Fulton County does not stand out in the Feeding America map while having the largest area of high rates in the tract level map. In this case, the low values in the northern half of the county counterbalance the high values of the southern half. A similar pattern is evident in Gwinnett County, which contains a wide range of values, but shows up as somewhat low in the Feeding America data. This highlights the value of a tract level analysis, which can potentially pinpoint areas of high need missed in broader scale studies.

Figure 4: Current tract level estimates from our two methodologies compared to county level rates from Feeding America's Map the Meal Gap study.



Change from current estimate to 2020

Figures 5 and 6 show changes in food insecurity rate between the current and 2020 estimates. The dots in these maps show the size of change, while the color shows the direction. Green dots show drops in food insecurity while grey and black dots show increases. Tracts with less than a 1% change are not included. As was the case in estimated rates, the two models show patterns that are largely similar. The majority of tracts with significant increases in food insecurity are located in the eastern and southern metro, in a line from southern Gwinnett County through Rockdale County into Henry County. The boundary between high and low rates in the urban core shows some movement as well, with rates decreasing in some areas south Fulton and Dekalb counties and increasing in the northern section of these counties. There are also significant increases predicted in Cherokee and Dawson counties in both models. Otherwise, food insecurity in non-metro counties is projected to stay largely unchanged in both models.

The main disagreement between these models is in the western metro, Cobb, Douglas, and Paulding counties. While the fixed effects model projects modest increases in food insecurity in these areas, the demographic metabolism method is more mixed. This is another area where a more detailed investigation into economic and demographic change in this area may be needed.

Figure 5: 2020 rate of food insecurity and change from current estimate for the fixed effects model

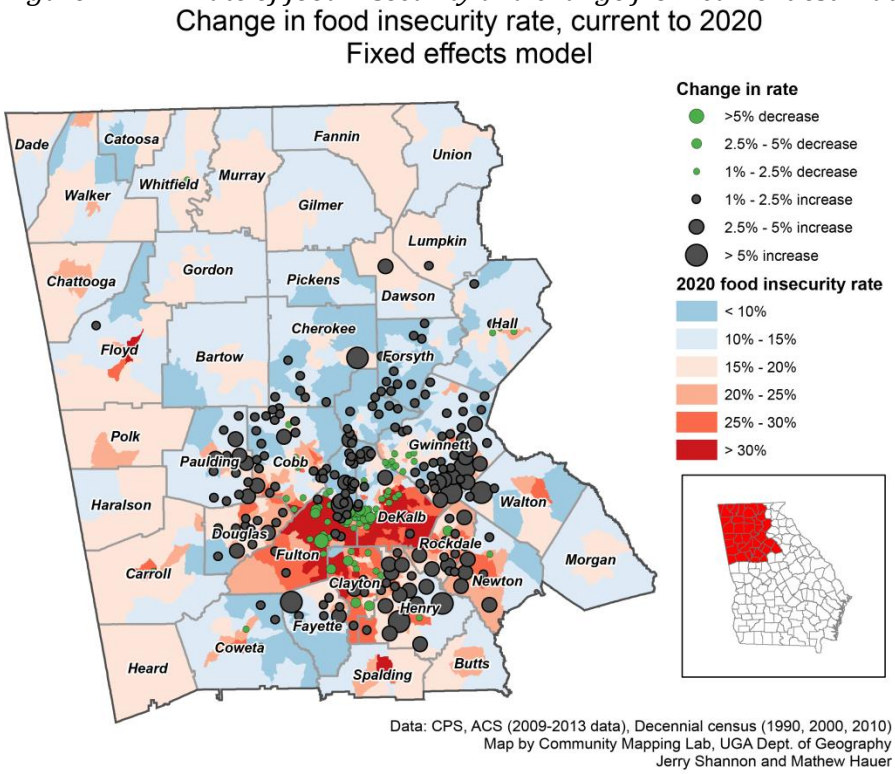
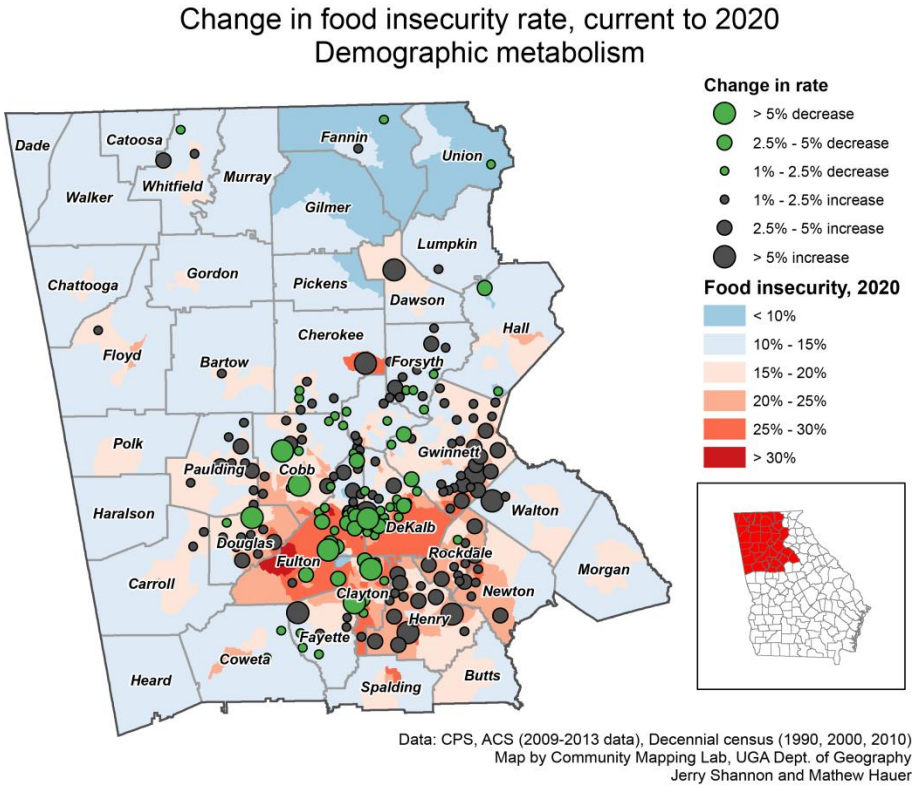
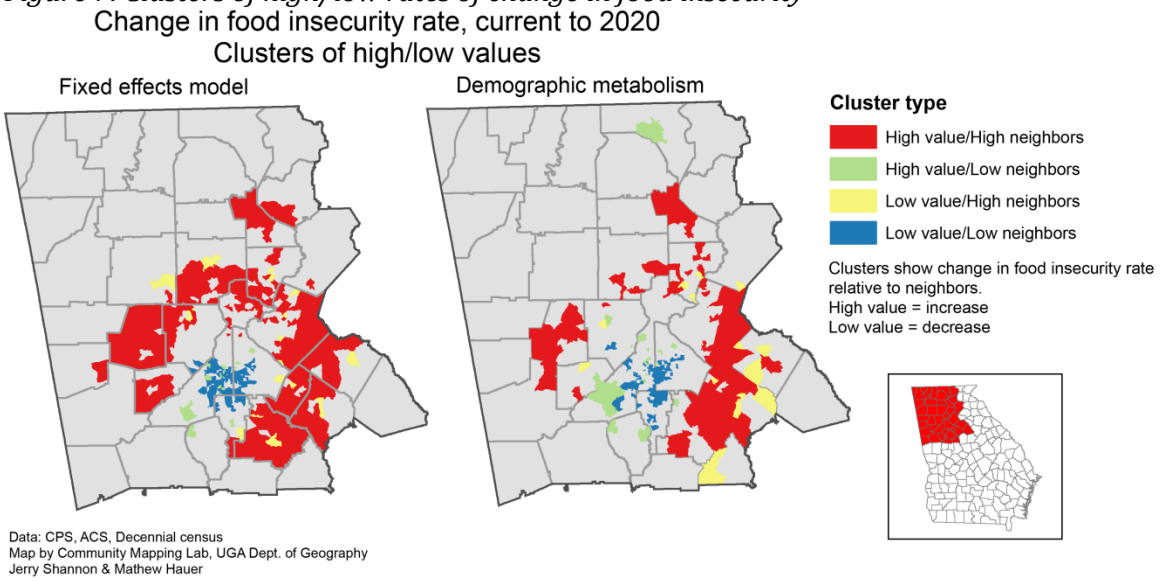


Figure 6: 2020 rate of food insecurity and change from current estimate for the demographic metabolism model



These patterns are confirmed in figure 7, which shows clusters of high and low values for change in food insecurity for both methodologies. These clusters were determined using local measures of spatial autocorrelation (LISA) analysis, which detects statistically significant spatial clusters of similar or contrasting values. Red values here show that increasing food insecurity in tracts along with their neighbors, while blue values show groups of tracts with declining food insecurity. Green and yellow values show high or low outlying tracts. These two methods have very similar results, showing increased food insecurity in suburban tracts and decreases in the urban core. An increase in food insecurity around Lumpkin and Dawson counties north of Atlanta also appears in both models.

Figure 7: Clusters of high/low rates of change in food insecurity



We also summed tract food insecure populations to the county level and calculated change in food insecurity rates at that scale. The results are shown in table 1. Again, there is a large degree of agreement between the two lists, with Dawson, Rockdale, Henry, Paulding and Cherokee counties seeing the highest increases in food insecurity. Clayton, Butts, and Union counties see decreases in food security.

Discussion

The results of this analysis point to the value of tract level estimation for food insecurity. While county level estimation highlights similar trends to those found in our tract level analysis, it conceals important variation within counties, especially those in the urban core such as Dekalb and Fulton. Tract level estimation is thus more useful for local level planning decisions for ACFB and other organizations addressing hunger within this region.

More substantively, these models highlight growing food insecurity on the urban fringe in the coming five year period. This pattern is most pronounced in the eastern and southern Atlanta suburbs, though increases are possible in other counties as well. We also project areas of increased need outside the metro, most notably in parts of Cherokee, Lumpkin, and Dawson counties. Food insecurity in other non-metro areas will most likely remain stable, however.

In the urban core, rates may decrease somewhat, especially along the current border between high and low need areas. It is important to note, however, that the largest food insecure populations in

both time periods will continue to be found in this urban core—in southern Fulton and DeKalb counties and in Clayton County. In these areas, significant investment will still be needed to address these communities' food needs.

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Table 1: County level rates of food insecurity ranked by change in rate

Fixed effects model		Demographic metabolism	
County	**Difference**	**County**	**Difference**
Dawson	2.40%	Dawson	4.30%
Henry	2.30%	Henry	2.00%
Rockdale	2.20%	Rockdale	1.70%
Newton	1.80%	Paulding	1.60%
Paulding	1.60%	Cherokee	1.50%
Cherokee	1.40%	Newton	1.40%
Gwinnett	1.30%	Gwinnett	1.10%
Fayette	1.10%	Lumpkin	0.60%
Lumpkin	0.80%	Forsyth	0.50%
Forsyth	0.80%	Fayette	0.20%
Douglas	0.80%	Douglas	0.20%
Walton	0.50%	Carroll	0.20%
Cobb	0.40%	Catoosa	0.10%
Catoosa	0.20%	Fulton	0.10%
Floyd	0.20%	Gordon	0.10%
Fulton	0.10%	Whitfield	0.10%
Murray	0.10%	Walton	0.00%
Bartow	0.10%	Floyd	0.00%
Haralson	0.10%	Murray	0.00%
Heard	0.10%	Bartow	0.00%
Morgan	0.10%	Haralson	-0.10%
Gordon	0.00%	Polk	-0.10%
Whitfield	0.00%	Fannin	-0.10%
Coweta	0.00%	Cobb	-0.20%
Chattooga	0.00%	Coweta	-0.20%
DeKalb	0.00%	Chattooga	-0.20%
Walker	0.00%	DeKalb	-0.20%
Pickens	0.00%	Dade	-0.20%
Gilmer	0.00%	Spalding	-0.20%
Carroll	-0.10%	Walker	-0.30%
Dade	-0.10%	Hall	-0.30%
Spalding	-0.10%	Union	-0.30%
Hall	-0.10%	Heard	-0.40%
Union	-0.10%	Pickens	-0.50%
Butts	-0.20%	Gilmer	-0.50%
Clayton	-0.20%	Morgan	-0.60%
Polk	-0.30%	Butts	-0.60%
Fannin	-0.40%	Clayton	-0.90%