

7-2020

## USING SPATIAL METHODS TO BETTER UNDERSTAND FOOD INSECURITY AND SNAP UNDER-PARTICIPATION IN TEXAS

RYAN RAMPHUL

Follow this and additional works at: [https://digitalcommons.library.tmc.edu/uthsph\\_dissertsopen](https://digitalcommons.library.tmc.edu/uthsph_dissertsopen)



Part of the [Community Psychology Commons](#), [Health Psychology Commons](#), and the [Public Health Commons](#)

---

### Recommended Citation

RAMPHUL, RYAN, "USING SPATIAL METHODS TO BETTER UNDERSTAND FOOD INSECURITY AND SNAP UNDER-PARTICIPATION IN TEXAS" (2020). *UT School of Public Health Dissertations (Open Access)*. 227. [https://digitalcommons.library.tmc.edu/uthsph\\_dissertsopen/227](https://digitalcommons.library.tmc.edu/uthsph_dissertsopen/227)

This is brought to you for free and open access by the School of Public Health at DigitalCommons@TMC. It has been accepted for inclusion in UT School of Public Health Dissertations (Open Access) by an authorized administrator of DigitalCommons@TMC. For more information, please contact [digcommons@library.tmc.edu](mailto:digcommons@library.tmc.edu).

USING SPATIAL METHODS TO BETTER UNDERSTAND FOOD INSECURITY  
AND SNAP UNDER-PARTICIPATION IN TEXAS

by

RYAN RAMPHUL, MS, BA

APPROVED:



---

LINDA HIGHFIELD, PHD



---

FRANCES LEE REVERE, PHD



---

SHREELA SHARMA, PHD



---

DEAN, THE UNIVERSITY OF TEXAS  
SCHOOL OF PUBLIC HEALTH

USING SPATIAL METHODS TO BETTER UNDERSTAND FOOD INSECURITY  
AND SNAP UNDER-PARTICIPATION IN TEXAS

by

RYAN RAMPHUL, MS,BA

APPROVED:



---

LINDA HIGHFIELD, PHD



---

FRANCES LEE RREVERE, PHD



---

SHREELA SHARMA, PHD

---

DEAN, THE UNIVERSITY OF TEXAS  
SCHOOL OF PUBLIC HEALTH

Copyright  
by  
Ryan Ramphul, MS, BA, PhD  
2020

USING SPATIAL METHODS TO BETTER UNDERSTAND FOOD INSECURITY  
AND SNAP UNDER-PARTICIPATION IN TEXAS

by

RYAN RAMPHUL  
MS, The University of Texas at Austin, 2010  
BA, The University of Texas at Austin, 2008

Presented to the Faculty of The University of Texas

School of Public Health

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS  
SCHOOL OF PUBLIC HEALTH  
Houston, Texas  
July, 2020

# USING SPATIAL METHODS TO BETTER UNDERSTAND FOOD INSECURITY AND SNAP UNDER-PARTICIPATION IN TEXAS

Ryan Ramphul, MS, PhD  
The University of Texas  
School of Public Health, 2020

Dissertation Chair: Linda Highfield, PhD, MS

The overall objective of this research is to use spatial methods to better understand food insecurity and SNAP under-participation in Texas.

Paper 1 assesses whether a sample of community dwelling Medicare and Medicaid beneficiaries, who screen positive for food insecurity at healthcare locations in Harris County, exhibit a spatial pattern in terms of where they live. In other words, it tests whether or not there are statistically significant neighborhood hot spots or cold spots of food insecurity against a null hypothesis of complete spatial randomness.

This approach is novel because it uses address-level data on patients who report being food insecure to test for statistically significant neighborhood hot spots or cold spots, instead of relying on extant factors like neighborhood poverty rates, or the presence of grocery stores. Using address-level food insecurity screening data is often difficult because few organizations screen for food insecurity, and even fewer are willing to share their data due to privacy concerns.

Paper 2 utilizes geographical information systems (GIS) to map census tract-level clusters and outliers of households that are eligible but not enrolled (EBNE) in the SNAP program. The implications of this analysis are vast. Knowing the locations of neighborhood-level clusters and outliers of SNAP EBNE households can inform interventions to address the “SNAP GAP” more effectively.

Additionally, this method of identifying neighborhood-level clusters and outliers of SNAP EBNE households can be applied to other safety net programs including Medicaid, the Children’s Health Insurance Program (CHIP), Healthy Texas Women, and the Women, Infant, and Children (WIC) Program.

## TABLE OF CONTENTS

<b>Background</b> .....	2
Literature Review.....	2
Public Health Significance.....	5
Hypothesis, Research Question, Specific Aims or Objectives .....	6
References.....	8
<b>Journal Article 1</b> .....	9
Mapping Neighborhood Hot Spots and Cold Spots of Food Insecurity in Medicare and Medicaid Beneficiaries in Harris County, Texas.. .....	9
Public Health Nutrition - Cambridge University Press.....	9
Background .....	9
Analytic Approach .....	13
Results .....	15
Discussion .....	<b>Error! Bookmark not defined.</b>
References.....	23
<b>Journal Article 2</b> .....	9
Mapping Census Tract-Level Clusters and Outliers of SNAP Under- Participation in Texas .....	27
CDC – Preventing Chronic Disease: Public Health Research, Practice, Policy.....	27
Background .....	32
Methods .....	34
Analytic Approach .....	36
Results .....	39
Discussion .....	45
References.....	48



## **BACKGROUND**

### **Literature Review**

The US Department of Agriculture (USDA) defines food insecurity as a lack of consistent access to enough food for an active, healthy life. They further break down the concept of food security into four levels: high food security, marginal food security, low food security, and very low food security. High food security households have no problems or anxiety about consistently accessing adequate food. Marginal food security households sometimes have problems or anxiety about accessing adequate food, but quality, variety, and quantity of their food are not substantially reduced. High food security and marginal food security households are considered food secure. Low food security households reduce the quality, variety, or desirability of diet without reducing food intake, and very low food security households disrupt their eating patterns and reduce their food intake. These households are considered food insecure.

Feeding America, a not-for-profit organization aimed at fighting food insecurity and hunger, points out that hunger and food insecurity are related concepts but differ in some aspects, with hunger referring to a personal, physical sensation of discomfort, and food insecurity describing a lack of available financial resources for food at the level of the household.

#### *Food insecurity is highly prevalent*

Food insecurity is highly prevalent in the US and especially in Greater Houston. In their examination of literature on food insecurity, entitled “Food Insecurity and Health Outcomes,” Gunderson and Ziliak (2015) note that the food insecurity rate for US

households was relatively steady, at about 11 percent for all households and almost 18 percent for those with children, but increased more than 30 percent during the Great Recession. Despite the official end of the Great Recession in June 2009, rates of food insecurity have remained elevated.

According to a report published by Rice University's Kinder Institute for Urban Research, entitled "Challenges of Social Sector Systemic Collaborations -What's Cookin in Houston's Food Insecurity Space," there are an estimated 724,750 food insecure individuals in Greater Houston. Additionally, the estimated food insecurity rate in Greater Houston is about 16.6 percent, which is roughly 4 percentage points above the national average. Over 500,000 Houston residents, moreover, live in USDA designated food desert areas.

*Food insecurity is associated with negative health outcomes*

A plethora of research suggests that food insecurity is not only highly prevalent, but associated with several poor health outcomes. Gunderson and Ziliak (2015) explore this research thoroughly. Regarding children, they found research indicating that food insecurity is associated with increased risk of birth defects, anemia, lower nutrient intakes, cognitive problems, aggression, and anxiety. They also found research indicating that food insecurity is associated with higher risks of children being hospitalized, having asthma, behavioral problems, depression, suicide ideation, poor oral health, and poor overall health.

Regarding non-senior adults, they found studies indicating that food insecurity is associated with decreased nutrient intakes, and increased rates of mental health problems, diabetes, hypertension and hyperlipidemia, worse outcomes on health exams, poor sleep outcomes, and poor overall health. Finally, regarding seniors, they found studies indicating

that food insecure seniors are more likely to be in poor health, depressed, and have limited daily activities compared to their food-secure peers. One of the studies they explored found that a senior who is marginally food insecure compared to one who is fully food secure has reduced nutrient intakes roughly equivalent to having \$15,000 less income per year. Another study found that the effects of being marginally food insecure limited activity of daily living (ADL) roughly the same as being fourteen years older.

More recent research paints an even more serious picture of the relationship between food insecurity and poor health outcomes. Shankar, Chung, & Frank's (2017) systematic review of 23 peer reviewed articles from developed countries found that household food insecurity, even at marginal levels, is associated with children's behavioral, academic, and emotional problems from infancy to adolescence. They recommend that behavioral health providers screen for food insecurity and intervene when possible, and that families who are identified as food insecure in primary care settings receive enhanced developmental behavioral assessment and intervention.

Recent studies also examine associations between food insecurity, increased sexual risk behaviors, and poor adherence to antiretroviral therapy (ART) among women living with HIV. In a systematic review, Chop et al (2017) found that food insecurity remains a challenge for many women living with HIV across diverse settings, resulting in risky coping strategies like transactional sex and sub-optimal ART adherence. They conclude that for HIV strategies to be effective, they must be layered with solutions to reduce hunger and food insecurity, especially for women.

Finally, studies suggest that food insecurity is associated with increase healthcare costs. Using a sample of 63,033 participants in the Canadian Community Health Survey to assess household food insecurity status, Tarasuk et al (2015) linked survey data with administrative health care data and found that household food insecurity was a robust predictor of health care utilization and costs, independent of other social determinants of health. They argue that policy interventions at the federal level designed to reduce household food insecurity could offset considerable public expenditures in health care.

### **Public Health Significance**

As the healthcare system in the United States gains a deeper understanding of how social factors affect health outcomes, the issue of food insecurity remains paramount. Health care providers increasingly screen patients for food insecurity, but few offer effective solutions for patients who screen positive. Often, patients who screen positive for food insecurity receive a resource sheet with the phone number to a food pantry, but little evidence suggests that patients actually connect with these resources. Even if they do connect with resources and receive help, masses of people who do not interact with health care system, remain food insecure.

With the understanding that health care costs can be reduced and population health can be improved, public health practitioners are increasingly interested in neighborhood-level approaches to address social determinants of health, like food insecurity. Spatial methods can help foster better understanding of the geographical aspects of social determinants of health, like food insecurity, and ultimately yield more precise outreach interventions.

## **Hypothesis, Research Question, Specific Aims or Objectives**

The objective of paper 1 is to assess whether a sample of community dwelling Medicare and Medicaid beneficiaries, who screen positive for food insecurity at healthcare locations in Harris County, exhibit a spatial pattern in terms of where they live. In other words, it seeks to test whether or not there are statistically significant, neighborhood-level hot spots or cold spots of food insecurity against a null hypothesis of complete spatial randomness.

This approach is novel because it uses address-level data on people who report being food insecure to test for statistically significant neighborhood hot spots or cold spots of food insecurity, instead of relying on extant factors like neighborhood poverty rates, or the presence of grocery stores. Using address-level food insecurity screening data is often difficult because few organizations screen for food insecurity and even fewer are willing to share their data due to privacy concerns.

The objective of paper 2 is to utilize geographical information systems (GIS) to map census tract-level clusters and outliers of households that are eligible but not enrolled (EBNE) in the SNAP program. The Houston SNAP Task Force, which is comprised of over 40 individuals from the public, private, and nonprofit sectors, was convened in 2017 by the Food Research and Action Center and the Food Trust to explore barriers to SNAP participation. The first recommendation under the Planning and Partnerships section of the report, “Closing the SNAP GAP,” is to create a strategic plan for reaching vulnerable populations and concrete goals to increase enrollment rates.

To reach vulnerable populations, they recommend a place-based approach to identify neighborhoods with disproportionately low SNAP participation rates, which is why this analysis is both actionable and novel. Once areas are identified, targeted SNAP application assistance outreach efforts, like The Texas Health and Human Services Commission's (HHSC) Community Partner Program, which collaborates with community organizations to help Texans apply for and manage their benefits, can be implemented more effectively.

## REFERENCES

- Chop, E., Duggaraju, A., Malley, A., Burke, V., Caldas, S., Yeh, P. T., ... & Kennedy, C. E. (2017). Food insecurity, sexual risk behavior, and adherence to antiretroviral therapy among women living with HIV: A systematic review. *Health care for women international*, 38(9), 927-944.
- Gundersen, C., & Ziliak, J. P. (2015). Food insecurity and health outcomes. *Health affairs*, 34(11), 1830-1839.
- Schuler, D. A., & Koka, B. R. (2019). Challenges of Social Sector Systemic Collaborations: What's Cookin' in Houston's Food Insecurity Space?.
- Shankar, P., Chung, R., & Frank, D. A. (2017). Association of food insecurity with children's behavioral, emotional, and academic outcomes: a systematic review. *Journal of Developmental & Behavioral Pediatrics*, 38(2), 135-150.
- Tarasuk, V., Cheng, J., De Oliveira, C., Dachner, N., Gundersen, C., & Kurdyak, P. (2015). Association between household food insecurity and annual health care costs. *Cmaj*, 187(14), E429-E436.

## **JOURNAL ARTICLE 1**

Mapping Neighborhood Hot Spots and Cold Spots of Food Insecurity in Medicare and Medicaid Beneficiaries in Harris County, Texas.

Public Health Nutrition – Cambridge University Press

### **BACKGROUND**

Little is known about the geographical nature of food insecurity, despite prior research examining associations between food environments, food access, and health outcomes. In 2008, the CDC produced the Modified Retail Food Environment Index (mRFEI), which indicates the percentage of healthy food retailers by census tract. The USDA later offered low income, low access (LILA) census tracts as a potential way to understand “food deserts,” where low income is defined by poverty rates and median family income, and low access by proximity to supermarkets or large grocery stores (Rhone et al, 2019). LILA and mRFEI census tracts are widely used in food environment studies, but assume that proximity to food retailers, or the presence of food retailers in a geographical area, is related to the ability to access food.

Studies show, however, that food choices and purchases are not necessarily associated with proximity to food outlets, but are likely a function of personal preferences, cultural factors, social norms, and the ability to afford foods (Lytle and Sokol, 2017; Brown and Brewster, 2015; Widener and Shannon, 2014; Jerry Shannon, 2018). Additional research validates this concept, showing that the introduction of low cost grocery stores into underserved “food desert” neighborhoods does not significantly impact shopping behaviors,



household food availability, or the health of residents (Ebel et al., 2015; Cummins et al, 2014; Widener, 2018, Ghosh-Dastidar et al, 2017).

Feeding America, a nation-wide non-profit organization aimed at mitigating hunger and food insecurity, offers one of the few methods of identifying neighborhood food insecurity that doesn't include a variable about proximity to food outlets, in its Map the Meal Gap tool. Defining food insecurity as the lack of reliable access to a sufficient quantity of affordable, nutritious food, the Mapping the Meal Gap tool estimates regional and area-level food insecurity prevalence using publicly available data on neighborhood unemployment, poverty, and other household characteristics (Feeding America, 2019). To our knowledge, however, no studies have explored the use of address-level food insecurity screening data from healthcare providers, and spatial clustering methods, to better understand neighborhood food insecurity.

This research assesses residential spatial patterns of Medicare and Medicaid beneficiaries, who screened positive for food insecurity at health care locations in Harris County, TX. In other words, it tests for statistically significant neighborhood-level clusters (hot spots or cold spots) of food insecurity against a null hypothesis of complete spatial randomness. This methodology is novel because it uses address-level data on individuals who report food insecurity, and spatial clustering methods, to identify areas where there may be more or less food insecure people than expected if food insecurity were randomly distribute throughout a community. This method differs drastically from other attempts to understand neighborhood food insecurity, which often use County, ZIP-code, or census tract-

level factors like poverty rates, or the presence of grocery stores, to estimate food insecurity prevalence.

## **METHODS**

### *Study Design and Sample*

This is a cross-sectional secondary data analysis of food insecurity screening data collected from Medicare and Medicaid beneficiaries who participated in the Center for Medicare and Medicaid Service's (CMS) Accountable Health Communities (AHC) Model, which is currently being piloted by the University of Texas Health Science Center at Houston. According to CMS, the AHC Model seeks to address gaps between clinical care and community services by testing whether identifying and addressing health-related social needs through screening, referral, and community navigation, impacts health care costs and reduces health care utilization (Alley, 2017). Screening is offered to all Medicare and Medicaid beneficiaries at several sites across Harris County. These sites include five hospitals in two large Texas Medical Center (TMC) health systems, and four outpatient clinics in one of the area's largest ambulatory groups.

Like many models that screen for food insecurity, The AHC model uses The Hunger Vital Signs screening tool. Hunger Vital Signs is a two question screening tool, suitable for clinical or community outreach use, that identifies risk for food insecurity if families answer that either or both of the following statements is "often true" or "sometimes true," versus "never true":

- “Within the past 12 months we worried whether our food would run out before we got money to buy more.”
- “Within the past 12 months the food we bought just didn’t last and we didn’t have money to get more.”

Children’s Health Watch, a nonpartisan network of pediatricians, public health researchers, and policy and child health experts validated the Hunger Vital Signs tool with a sample of 30,000 caregivers. They found excellent sensitivity (97%) and specificity (83%) with the Hunger Vital Signs tool compared to the much longer US Household Food Security Scale (HFSS) screening tool, which is considered the “gold standard” in assessment and identification of food security.

After obtaining IRB approval from the University of Texas Health Science Center at Houston’s Committee for the Protection of Human Subjects, we pulled a total of 7,658 food insecurity screening records, collected at AHC sites in Harris County, from August 2018–January 2020. Participants’ home addresses were geocoded using ArcGIS Pro Street Map Premium. Partial addresses, unrecognizable addresses, PO Box addresses, and addresses that fall outside of Harris County were excluded, providing a sample size of 6,649 useable address records. Of the 6,649 useable addresses 6,523 records geocoded successfully to a street address, while 126 addresses were manually matched to a street address. After addresses were mapped using ArcGIS, they were analyzed spatially. Cases are participants who screen positive for food insecurity (n=3,589) and controls are participants who screen negative food insecurity (n=3,060).

### *Analytic Approach*

Described in Martin Kulldorff's, *A Spatial Scan Statistic* (1997), Kulldorff's Spatial Scan Statistic was used to test whether or not there are statistically significant neighborhood clusters (hot spots or cold spots) of positive food insecurity screens within the study population. Kulldorff's Spatial Scan Statistic compares observed cases in an area to expected cases, based on computationally intensive data simulations, and is widely used in public health and crime analysis research. In a systematic review of spatial methods in epidemiology, Auchincloss et al (2012) recognize Kulldorff's spatial scan statistic as the preferred local cluster detection method in the studies examined in their review. They point to the fact that Kulldorff's spatial scan statistic can adjust for multiple testing and heterogeneous background population densities along with other confounding variables, is applicable to both point and aggregated data, and has been adapted to detect noncircular clusters, as potential reasons for its widespread use (Auchincloss et al, 2012).

The Bernoulli purely spatial model for binomial data was run in SaTScan version 9.6, developed by Martin Kulldorff, to spatially compare cases (people who screened positive for food insecurity) to controls (people who screen negative for food insecurity). SaTScan does this by creating a series of circular windows over each case address in the study area and evaluating each window as a possible cluster. The radius of the window varies continuously in size, from zero to an upper limit specified by the user. The scan statistic can detect windows where there are more cases within the cluster than outside, or suspected "hot spots," as well as suspected "cold spots," where there are fewer cases within the cluster than outside. Statistical significance of clusters is tested with a likelihood ratio test, using the null

hypothesis of no clustering (random distribution), and a p-value based on 999 Monte Carlo simulations.

The default in SaTScan is to look for clusters covering up to half the population at risk. In Harris County, that can be a very large area, containing almost half of the county. To avoid the detection of such large uninformative clusters, we set a smaller maximum on the cluster size of 25% of the population at risk, per the recommendations in SaTScan Tutorial #2 The Bernoulli Spatial Scan Statistic for Birth Defect Data (Talbot, Kumar, & Kulldorff, 2015).

We selected the default option, to report clusters with no geographical overlap. With this option, secondary clusters are only reported if they do not overlap with a previously reported cluster. This is the most restrictive option, presenting the fewest number of clusters (Kulldorff, 2015). We also selected the option to group non-overlapping clusters in a manner that maximizes the Gini coefficient, which is a measure of statistical dispersion. As Han et al point out in “Using Gini Coefficient to Determine Optimal Cluster Reporting Sizes for Spatial Scan Statistics,” the Gini coefficient can identify a more refined collection of non-overlapping clusters to report so that there is a big difference in rates between the cluster and non-cluster areas (2016).

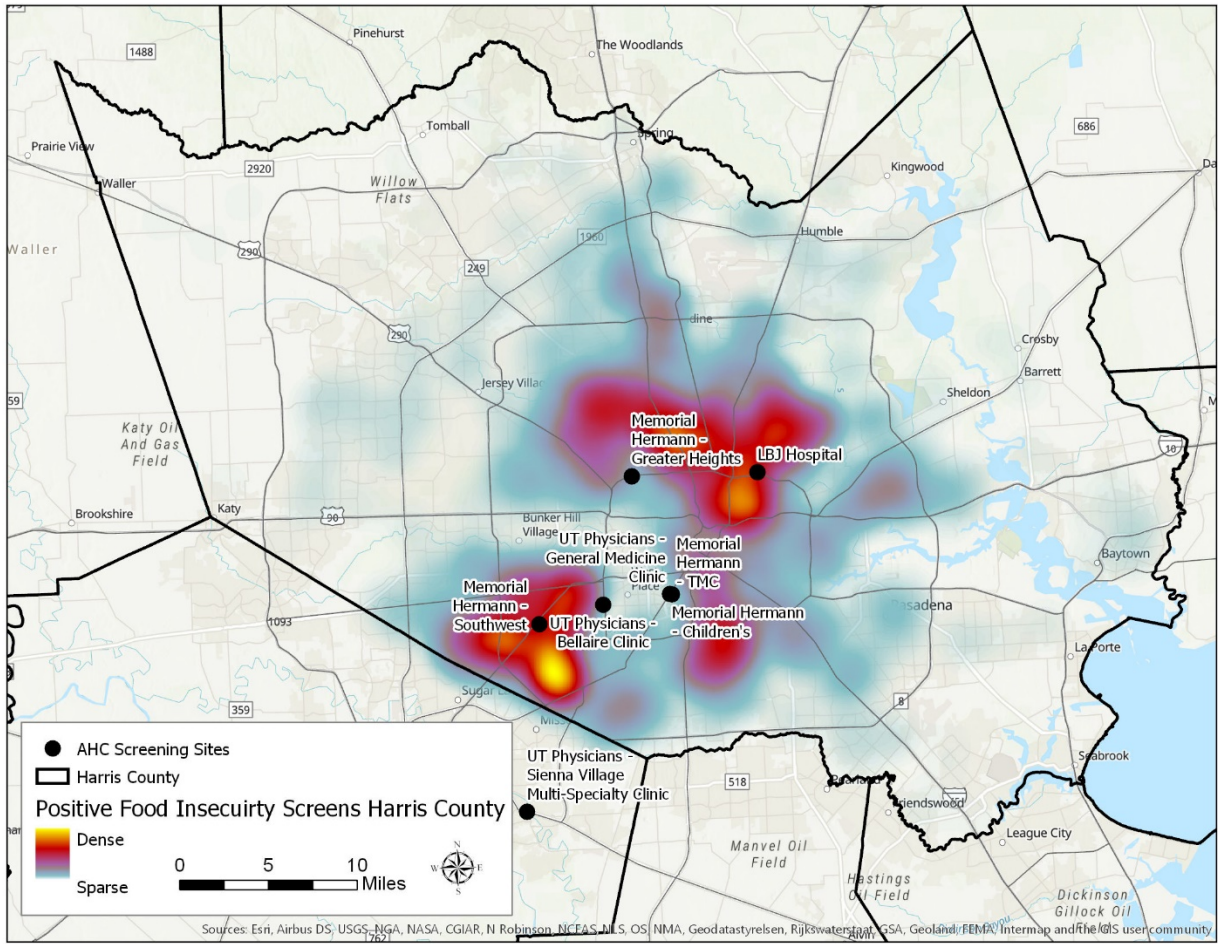
Since a wealth of research suggests that poverty (not proximity to grocery stores) is a potential predictor of area food insecurity, we overlaid any statistically significant clusters we found with area poverty rates for visual assessment purposes.

## RESULTS

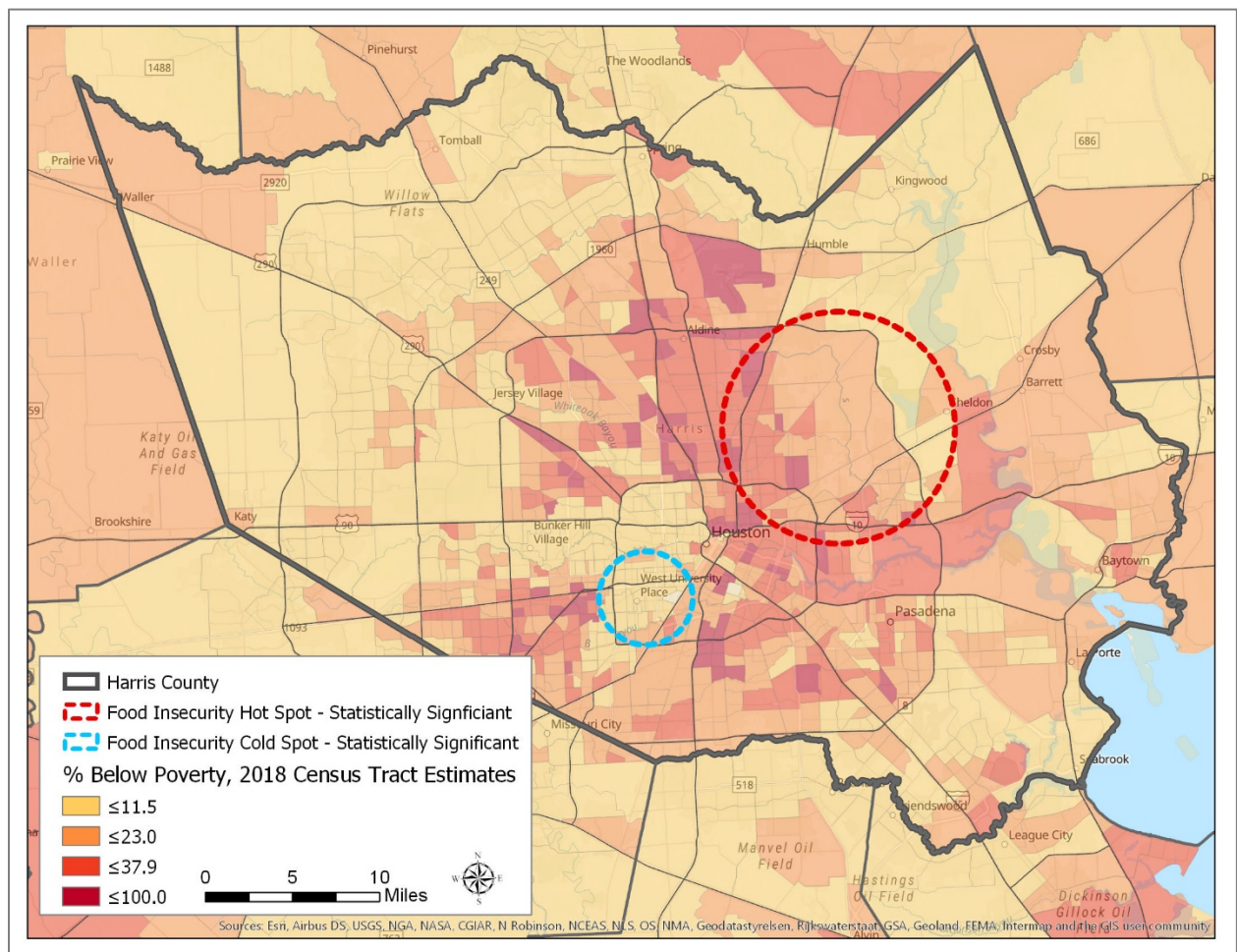
The density surface map in Figure 1 shows areas of Houston where positive food insecurity screens are densest. The hot/cold spot map in Figure 2, on the other hand, compares positive food insecurity screens to expected positive food insecurity screens based on data-intensive simulations. Out of eight suspected clusters of food insecurity, we found two statistically significant clusters.

A statistically significant cold spot of food insecurity was found in the West University-Medical Center area of Houston, where there were only 13 positive food insecurity cases compared to 45 expected cases (Table 1). Additionally, we found a large statistically significant hot spot of food insecurity on the northeast side of Houston/Harris County, where there were 686 positive food insecurity screens compared to 602 expected cases (Table 1). When we visually examined these hot/cold spots in relation to census tract-level poverty rates, the cold spot was located in an area with relatively low poverty rates, while the hot spot covered an area with higher poverty rates (Figure 2).

**Figure 1: Density Surface Map of Positive Food Insecurity Screens**



**Figure 2: Food Insecurity Hot/Cold Spots Overlaid with Neighborhood Poverty Rates**





**Table 1: Statistically Significant Clusters (Hot Spots and Cold Spots) of Food Insecurity in Harris County**

	Cluster 1: Cold Spot	Cluster 2: Hot Spot
<b>Coordinates / radius</b>	(29.717009 N, 95.428978 W) / 4.32 km	(29.853773 N, 95.239930 W) / 10.72 km
<b>Gini cluster</b>	Yes	Yes
<b>Population</b>	84	1115
<b>Number of cases</b>	14	686
<b>Expected cases</b>	45.34	601.86
<b>Observed / expected</b>	0.29	1.14
<b>Relative risk</b>	0.28	1.17
<b>Percent cases in area</b>	15.5	61.5
<b>Log likelihood ratio</b>	27.242225	15.507471
<b>P-value</b>	0.000000012	0.0015

## DISCUSSION

This analysis extends the knowledge base on neighborhood food insecurity in several ways. To our knowledge, this is the first study to use address-level food insecurity screening data from healthcare systems to identify neighborhood statistical clusters (hot spots and cold spots) in a major metropolitan area. This offers a different method of examining neighborhood food insecurity than previous studies, which often rely on ZIP code or census-tract data.

Ray, Kulldorff, and Asgari, point out that epidemiologists often describe and map health data by geographic units such as state, county, zip code, or census tract, but these maps are quantitatively difficult to assess due to the arbitrariness of the geographic boundaries and the potentially large differences in the size of the population contained within each unit (2016). They argue that the spatial scan statistic avoids these problems by using a rigorous statistical approach to identifying statistically significant clusters and adjusting for multiple testing (Ray, Kulldorff, and Asgari, 2019). Meliker et al support this conclusion in

their cluster analysis of early stage breast cancer in Michigan, finding that address-level data identified spatial clusters of breast cancer that were not detected when aggregated into census block groups, census tracts, or legislative districts (2009).

Additionally, this analysis adds to the knowledge base of neighborhood food insecurity by providing evidence that food insecurity, at least among people screened at healthcare providers in Harris County, exhibits spatial clustering patterns versus a null hypothesis of being randomly distributed throughout the region. This is noteworthy because little is understood about the geographical aspects of food insecurity. Previous studies found that food insecurity was prevalent in “food deserts,” but a wealth of research now suggests otherwise (Ebel et al., 2015; Cummins et al, 2014; Widener, 2018, Ghosh-Dastidar et al, 2017).

Previous research also found that neighborhoods with high poverty rates were likely to have a higher proportion of food insecure households, but new research paints a more nuanced picture, suggesting that as neighborhood disadvantage increases, higher-SES families’ risk of food insecurity increases, but lower-SES families’ risk decreases (Denny, Kimbro, & Sharp, 2018). With such mixed results in the literature on the geographical aspects of food insecurity, scientifically testing whether or not food insecurity exhibits a spatial pattern at all, is crucial first step in trying to understand the spatial aspects of neighborhood food insecurity.

Finally, this analysis is highly actionable because it provides a methodology for identifying areas that have more food insecure people than expected. With this kind of precision, targeted interventions can be deployed in a manner that maximizes their efficiency.

In “A Systematic Review of the Evaluation of Interventions to Tackle Children’s Food Insecurity” Holley and Mason argue that the evidence base on food insecurity interventions is both mixed and lacking in robustness (2019). De Marchis et al. further in “Interventions Addressing Food Insecurity in Health Care Settings: A Systematic Review,” that although a growing base of literature explores health care–based FI interventions, the low number and low quality of studies limit inferences about their effectiveness (2019). Neither of these systematic reviews, however, examine studies about food insecurity interventions targeted to specific geographies based on precision location analytics.

If targeted more precisely, neighborhood food insecurity interventions might yield more positive results. As Kolak, Abrahham, & Talen (2019) point out in their analysis of type 2 diabetes clusters in a primary care population in Chicago, much effort has been made by public health agencies to geographically plot chronic diseases at the national, state, and city levels, but information is limited on how disease is distributed in smaller geographic areas or populations. They argue that adapting spatial methods to smaller, more localized populations, may provide additional strategies for identifying localized areas of health risk for targeting interventions and improving care in smaller panel populations.

The primary limitation in this analysis is the sample size of participants screened for food insecurity. Ideally, there would be more data collection sites and a larger sample of screens. Additionally, the AHC model only screens people enrolled in Medicaid and Medicare, excluding people who are uninsured or do not access the healthcare care system. This limits the sample and adds selection bias. Finally, the data used in this analysis only

considers screening results for food insecurity and does not directly assess neighborhood disadvantage, which could offer more insight.

Aside from providing a novel and actionable method for understanding neighborhood food insecurity, a key strength of this analysis is data quality. We are unaware of any analysis of a universal offer to screen approach for food insecurity, such as the one used in the AHC model, where every Medicaid or Medicare patient seen at participating clinics is offered a chance to be screened. CMS launched the 5-year, \$157 million AHC program in part because despite calls for obtaining an expanded social history at the point of care, most health care systems lack the infrastructure and incentives to develop comprehensive screening-and-referral protocols (Alley et al, 2018).

In addition, studies suggest that screening for food insecurity at healthcare providers might yield more accurate results than screening for it in other settings. In a systematic review of health care-based screening for food insecurity, most studies reported that patients were comfortable being asked about food insecurity and social needs in clinical settings, as it made them feel cared for by their providers (Torres et al, 2017). Additionally, reassurance that providers were asking about food insecurity and social needs in order to help patients address these issues, often alleviated concerns from caregivers who might fear being reported to social services for not being able to feed their children (Torres et al, 2017). This might explain why of the 6,649 records in our sample, 3,589 (54%) screened positive for food insecurity, a much higher food insecurity rate than Greater Houston which is an estimated 16.6 percent (Schuler and Koka, 2019).

Future research should explore statistical hot/cold spots more thoroughly, comparing them to other areas within cities, counties, and states. Specifically, they should explore what factors in these areas (poverty rates, housing characteristics, racial/ethnic makeup, employment, etc.) can explain why they have more or less positive food insecurity screens than would be expected, given that other areas of town might have similar extant characteristics. In addition, future research should explore this type of analysis with a wider sample of participants, like uninsured patients, commercially insured patients, or even people outside of a clinical setting, using survey mechanisms like the American Community Survey or the Health of Houston Survey.

## REFERENCES

- Alley, D. E., Asomugha, C. N., Conway, P. H., & Sanghavi, D. M. (2016). Accountable health communities—addressing social needs through Medicare and Medicaid. *N Engl J Med*, 374(1), 8-11.
- Auchincloss, A. H., Gebreab, S. Y., Mair, C., & Diez Roux, A. V. (2012). A review of spatial methods in epidemiology, 2000–2010. *Annual review of public health*, 33, 107-122.
- Brown, D. R., & Brewster, L. G. (2015). The food environment is a complex social network. *Social Science & Medicine*, 133, 202-204.
- De Marchis, E. H., Torres, J. M., Benesch, T., Fichtenberg, C., Allen, I. E., Whitaker, E. M., & Gottlieb, L. M. (2019). Interventions addressing food insecurity in health care settings: a systematic review. *The Annals of Family Medicine*, 17(5), 436-447.
- Denney, J. T., Kimbro, R. T., & Sharp, G. (2018). Neighborhoods and food insecurity in households with young children: a disadvantage paradox?. *Social Problems*, 65(3), 342-359.
- Elbel, B., Moran, A., Dixon, L. B., Kiszko, K., Cantor, J., Abrams, C., & Mijanovich, T. (2015). Assessment of a government-subsidized supermarket in a high-need area on household food availability and children's dietary intakes. *Public health nutrition*, 18(15), 2881-2890.

- Flint, E., Cummins, S., & Matthews, S. (2013). Do perceptions of the neighbourhood food environment predict fruit and vegetable intake in low-income neighbourhoods?. *Health & place*, 24, 11-15.
- Ghosh-Dastidar, Madhumita, Gerald Hunter, Rebecca L. Collins, Shannon N. Zenk, Steven Cummins, Robin Beckman, Alvin K. Nugroho, Jennifer C. Sloan, and Tamara Dubowitz. "Does opening a supermarket in a food desert change the food environment?." *Health & place* 46 (2017): 249-256.
- Han, J., Zhu, L., Kulldorff, M., Hostovich, S., Stinchcomb, D. G., Tatalovich, Z., ... & Feuer, E. J. (2016). Using Gini coefficient to determining optimal cluster reporting sizes for spatial scan statistics. *International journal of health geographics*, 15(1), 27.
- Holley, C. E., & Mason, C. (2019). A systematic review of the evaluation of interventions to tackle children's food insecurity. *Current nutrition reports*, 8(1), 11-27.
- Kolak, M., Abraham, G., & Talen, M. R. (2019). Peer Reviewed: Mapping Census Tract Clusters of Type 2 Diabetes in a Primary Care Population. *Preventing chronic disease*, 16.
- Kulldorff, M. (1997). A spatial scan statistic. *Communications in Statistics-Theory and methods*, 26(6), 1481-1496.
- Kulldorff, M. (2015). SaTScan (TM) User Guide for version 9.6. *URL: [http://www. SaTScan.org](http://www.SaTScan.org)*.

Lytle, L. A., & Sokol, R. L. (2017). Measures of the food environment: A systematic review of the field, 2007–2015. *Health & place*, 44, 18-34.

Meliker, J. R., Jacquez, G. M., Goovaerts, P., Copeland, G., & Yassine, M. (2009). Spatial cluster analysis of early stage breast cancer: a method for public health practice using cancer registry data. *Cancer Causes & Control*, 20(7), 1061-1069.

Morrissey, T. W., Oellerich, D., Meade, E., Simms, J., & Stock, A. (2016). Neighborhood poverty and children's food insecurity. *Children and Youth Services Review*, 66, 85-93.

Ray, G. T., Kulldorff, M., & Asgari, M. M. (2016). Geographic clusters of basal cell carcinoma in a northern California health plan population. *JAMA dermatology*, 152(11), 1218-1224.

Rhone, A., Ver Ploeg, M., Williams, R., & Breneman, V. (2019). *Understanding Low-Income and Low-Access Census Tracts Across the Nation: Subnational and Subpopulation Estimates of Access to Healthy Food* (No. 1476-2019-1856).

Shannon, J. (2016). Beyond the supermarket solution: Linking food deserts, neighborhood context, and everyday mobility. *Annals of the American Association of Geographers*, 106(1), 186-202.



Talbot, T., Kumar, S., & Kulldorff, M. (2015). SatScan Tutorial #2 The Bernoulli Spatial

Scan Statistic for Birth Defect Data. *URL:*

<https://www.satscan.org/tutorials/nysbirthdefect/SaTScanTutorialNYSBirthDefect.pdf>

Schuler, D. A., & Koka, B. R. (2019). Challenges of Social Sector Systemic Collaborations:

What's Cookin' in Houston's Food Insecurity Space?.

Torres, J., De Marchis, E., Fichtenberg, C., & Gottlieb, L. (2017). Identifying food insecurity

in health care settings: a review of the evidence. San Francisco, Calif., SIREN

Network (UCSF).

Widener, M. J., & Shannon, J. (2014). When are food deserts? Integrating time into research

on food accessibility. *Health & place*, 30, 1-3.

Widener, M. J. (2018). Spatial access to food: Retiring the food desert metaphor. *Physiology*

& behavior, 193, 257-260.

## **JOURNAL ARTICLE 2**

### **Mapping Census Tract-Level Clusters and Outliers of SNAP Under-Participation in Texas**

#### **CDC – Preventing Chronic Disease: Public Health Research, Practice, and Policy**

### **BACKGROUND**

Several studies confirm that the Supplemental Nutrition Assistance Program (SNAP) is effective at mitigating food insecurity. Ratcliffe, McKernan, & Zhang (2011) found that receipt of SNAP benefits reduced the likelihood of being food insecure by roughly 30% and reduced the likelihood of being very food insecure by 20%. Mabli and Ohls (2015) compared surveys from new entrants into the SNAP program to surveys from people who participated for roughly 6 months, and found that SNAP participation decreased food insecurity by 6-17%. Gray and Cunnyingham (2016), furthermore, found that participation in the SNAP program for 6 months was associated with a decrease in food insecurity by roughly 5 to 10 percentage points, including among food insecure households with children.

*There is under-participation in the SNAP program, or a “SNAP GAP.”*

Gray and Cunnyingham (2016) show, of the 51 million individuals eligible for SNAP in 2014, only 42 million (83%) participated. Additionally, they found that from 2013 to 2014 the number of SNAP participants decreased by about 2 percent, while the number of eligible individuals increased by 1%. Under-participation in SNAP is even more pronounced in Texas, which ranks 46th in the nation for participation among SNAP-eligible people (The Houston SNAP Task Force, 2018). From 2010–2014 an estimated 258,000 Houston residents

were likely eligible for SNAP but not participating, despite significant research demonstrating the SNAP program's positive impacts on food insecurity, population health, economic development, and quality of life people (The Houston SNAP Task Force, 2018).

### *Spatial analysis of the SNAP program*

A growing body of literature explores spatial aspects of the SNAP program. Jerry Shannon (2014) utilized zip code-level SNAP data for the Twin Cities metro area to show that while supermarkets receive almost all SNAP benefits in suburban areas, they receive a smaller share of SNAP redemptions in low-income neighborhoods. In addition, he found that low income neighborhoods receive more benefits than are spent at neighborhood food retailers, confirming that low-income residents often travel outside their neighborhoods to get food, regardless of the presence or absence of supermarkets.

Slack and Myers (2013) utilized statistical clustering methods to find that counties where SNAP use climbed highest during the Great Recession were not randomly distributed across the nation. Additionally, they found that areas where home foreclosures and unemployment were most pronounced were also the places where SNAP use rose most during the recession. In a similar analysis, Albert and Lim (2019) analyzed geographically varying spatial clusters of state unemployment rates and Temporary Assistance for Needy Family Program (TANF) caseload growth rates, and found strong state-level spatial clusters in unemployment rates and TANF maximum aid. Finally, in "Food for Thought: Analyzing Public Opinion on the Supplemental Nutritional Assistance Program, Chappelka, Oh, & Scott (2019) tracked public opinion on the SNAP program in the news, social media outlets, and

the voting records of elected representatives and found statistical clustering of negative reporting on the SNAP program in Midwestern states.

While studies have explored spatial aspects of the SNAP program, to our knowledge, no spatial studies have explored statistical clusters of under-participation at a high spatial resolution, like census tracts. The objective of this cross-sectional descriptive study is to utilize geographical information systems (GIS) and spatial analysis methods to map census tract-level clusters and outliers of households that are eligible but not enrolled (EBNE) in the SNAP program. Clusters of high household SNAP EBNE are considered “hot spots,” and clusters of low household SNAP EBNE are considered “cold spots.” Understanding neighborhood-level aspects of SNAP participation can greatly inform outreach efforts.

## **METHODS**

We conducted analysis on census tracts throughout Texas to explore clusters and outliers of SNAP EBNE throughout the state. Additionally, we conducted analysis on census tracts within Harris County, Texas to explore clusters and outliers in the state’s most populous region. Harris County is located in southeast Texas, near Galveston Bay. With a population over 4 million people, it is the third most populous county in the United States. Harris County contains most of the boundaries of the City of Houston, which is the largest city in Texas and fourth largest city in the United States.

### *Data Sources*

In general, SNAP benefits in Texas are for low income families with children, pregnant women, or disabled people (SNAP Food Benefits - How to Get Help, 2019). Adults

with no children can still receive SNAP benefits, but there are time limits if they don't work or participate in a job training program. Additionally, applicants must have lived in the United States for no less than 5 years.

The US Census Bureau's American Community Survey (ACS) provides 5-year, 2018 census tract estimates of households below the federal poverty level, and households below the federal poverty level who are not receiving SNAP. With these variables, we calculated the percentage of households below the federal poverty level, who are not enrolled in the SNAP program for each census tract in Texas. This is a conservative proxy for the percentage of eligible but not enrolled (EBNE) households by census tract, because in Texas, households can make less than or equal to 130 percent of the federal poverty level and still qualify for the SNAP program. We also use ACS 5-year census tract estimates of household density, median family income, and percentage of households below the federal poverty level to compare hot spot census tracts and cold spot census tracts to other census tracts.

ACS 5-year census tract estimates are derived from the largest sample sizes of all ACS estimates, providing the most reliable community survey data offered at the census tract level (US Census Bureau, 2019). Census tracts, furthermore, are a desirable geography because they serve as the fundamental unit employed by a myriad of public agencies to create local administrative areas, and are used to designate diverse policy-related entities, including "Urban Empowerment Zones," "Medically Underserved Areas," "Qualified Census Tracts" for the low-income housing credit, and "Poverty Areas," where 20% or more of the population is below the U.S. poverty line (Krieger, 2006).

### *Analytic Approach*

While uncertainty is unavoidable when working with ACS data, we used Empirical Bayesian Smoothing to strengthen uncertain estimates and weaken outliers in our calculation of the percentage of SNAP EBNE households by census tract. Empirical Bayesian Smoothing adjusts values toward the mean of the observed data with the amount of shrinkage toward the mean being inversely proportional to the size of the overall population at risk (Dahlberg, 2016). Census tracts with large populations experience smaller amounts of adjustment toward the mean than census tracts with small populations (Anselin, 2005).

Next, we utilized the local indicators of spatial association (LISA) statistic, which tests for spatial randomness by looking for clusters of high values, low values, and outlier values in a geographical data set (Anselin, 1995). Specifically, Anselin's Local Moran's I statistic looks for clusters of high values "hot spots" and low values "cold spots" by determining "neighborhoods" around each census tract in a dataset, and identifies outliers by comparing census tracts to their own "neighborhoods" (Anselin, 1995).

Using the Environmental Science Research Institute's (ESRI) ArcGIS Pro Version 2.2.0 software, we ran the Cluster and Outlier Analysis Tool. Given a set of census tracts and an analysis field (percentage of SNAP EBNE households), the Cluster and Outlier Analysis tool calculates a Local Moran's I value, a z-score, a pseudo p-value, and a code representing the cluster type for each statistically significant feature. A positive value for I indicates that a census tract has neighboring census tracts with similarly high or low percentages of SNAP EBNE households; this feature is part of a cluster. A negative value for I indicates that a

census tract has neighboring census tracts with dissimilar values; this census tract is an outlier.

To test statistical significance, Monte-Carlo simulations are run with 9,999 permutations that randomly rearrange the neighborhood values around each census tract and calculate the Local Moran's I value of the random data. A pseudo p-value is calculated by determining the proportion of Local Moran's I values generated from permutations that display more clustering than the original data. If the pseudo p-value is less than 0.05, the data displays statistically significant clustering.

While several strategies exist to determine the “neighborhood” around each census tract, we used the k-nearest neighbor method, with eight neighbors. Eight neighbors are recommended as a general rule of thumb in cluster and outlier analysis (ESRI). Using this method, the eight closest census tracts to the target census tract are considered its “neighborhood,” and are included in its computations. The vast majority of census tracts in our study area were calculated with eight neighbors, but census tracts with zero estimated households below the poverty level were excluded from calculations, resulting in a handful of census tracts having less than 8 neighbors in their Local Moran's I calculations. No census tracts, however, were calculated with less than 4 neighbors.

The k-nearest neighbors method is used in several studies aimed at identifying clusters and outliers of health-related factors in large geographical areas because other distance-based methods of determining a “neighborhood” tend to make too many neighbors in urban areas and too few neighbors in rural areas (Anselin 2002). These studies include cluster detection and spatial outlier analysis of teen birth rates in the US, by Khan et al

(2017), analysis of spatial clusters of child lower respiratory illnesses by Beamer et al (2016), and analysis of cluster detection for childhood leukemia incidence in Ohio, by Wheeler (2007).

#### *Kruskal-Wallis One-Way Analysis of Variance*

After implementing Anselin's Local Moran's I statistic for each census tract in the dataset, ArcGIS Pro's Cluster and Outlier Analysis tool labels census tracts as hot spots (HH), cold spots (LL), outliers (LH, HL), or not significant. To conduct further analysis, we consolidated these groups into three categories: hot spots (HH), cold spots, (LL), and all other (AO+LH+HL); where AO represents non-significant census tracts, LH represents cold outliers, and HL represents hot outliers. We then compared the median values of social indicators in hot spot and cold spot tracts with the median values in all other tracts using Kruskal-Wallis One-Way Analysis of Variance.

The census-tract level social indicators we examined include households per square mile, median household income, and percent of households below the federal poverty level. We examined households per square mile because more densely populated census tracts are likely to be in urban areas and prior research suggests that SNAP participation rates in urban areas are significantly lower than rural participation rates (Bailey, 2014). We examined median household income and the percent of households below the federal poverty level because research suggests that poorer people tend to enroll in SNAP at higher rates than people who are slightly less poor, but still eligible (Pinard et al, 2017).

Since all three socio-demographic variables were not normally distributed (skewed right) based on histograms and the Kolmogorov-Smirnov p-values, non-parametric testing



was utilized (Kruskal-Wallis test). Medians, interquartile ranges (IQR) and p-values were reported, and pairwise comparison was adjusted using the Bonferroni correction in the post hoc analysis. Table 1 reports the difference across three groups (HH+LL+AO) in Texas and Harris County, and Table 2 shows pairwise comparisons of selected neighborhood characteristics in Texas and Harris County.

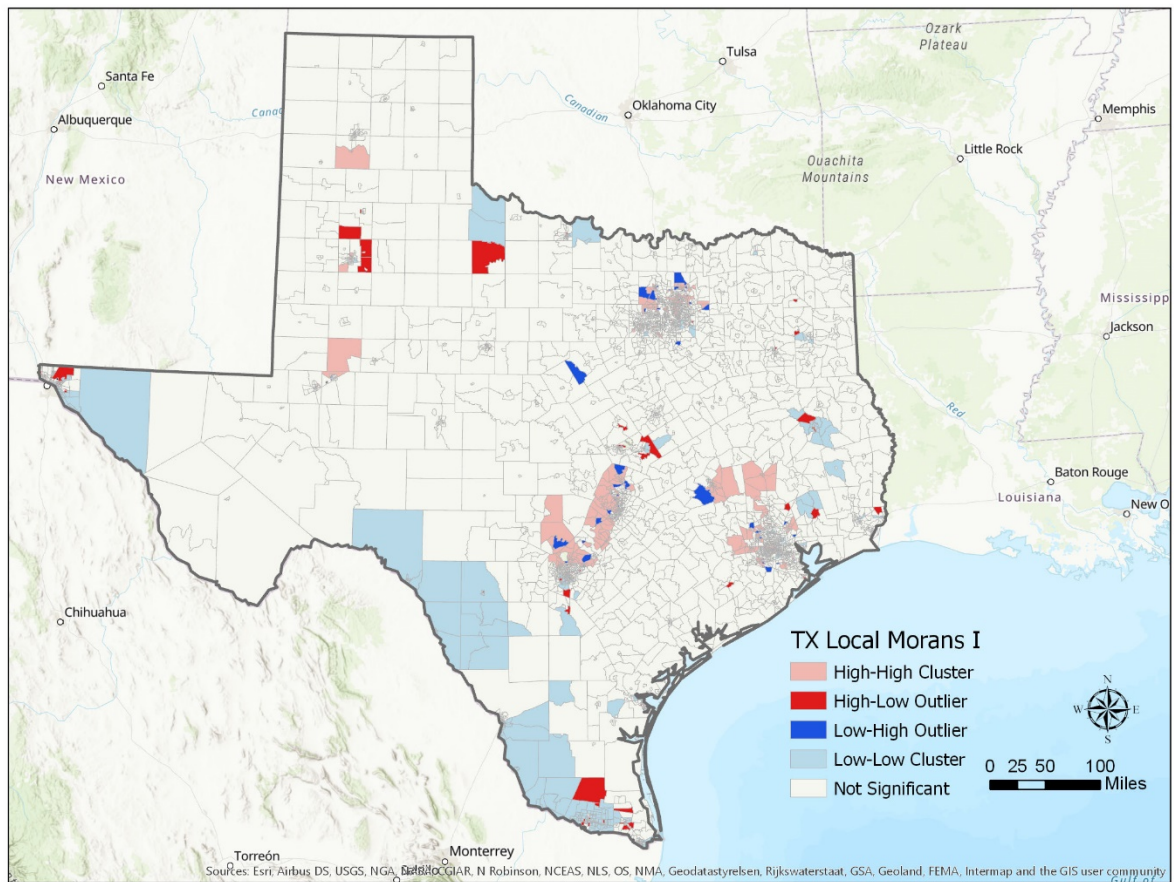
## RESULTS

Of 5,194 census tracts in Texas we found 627 hot spots, or census tracts with a statistically significant high percentage of SNAP EBNE households, surrounded by other census tracts with a significantly high percentage of SNAP EBNE households, demarcated as “HH.” We also found 529 cold spots, or census tracts with a statistically significant low percentage of SNAP EBNE households, surrounded by other census tracts with a significantly low percentage of SNAP EBNE households, demarcated as “LL.” When we re-ran the analysis with only census tracts in Harris County, we found similar proportions. Of 781 census tracts, 102 were hot spots “HH” and 80 were cold spots “LL.”

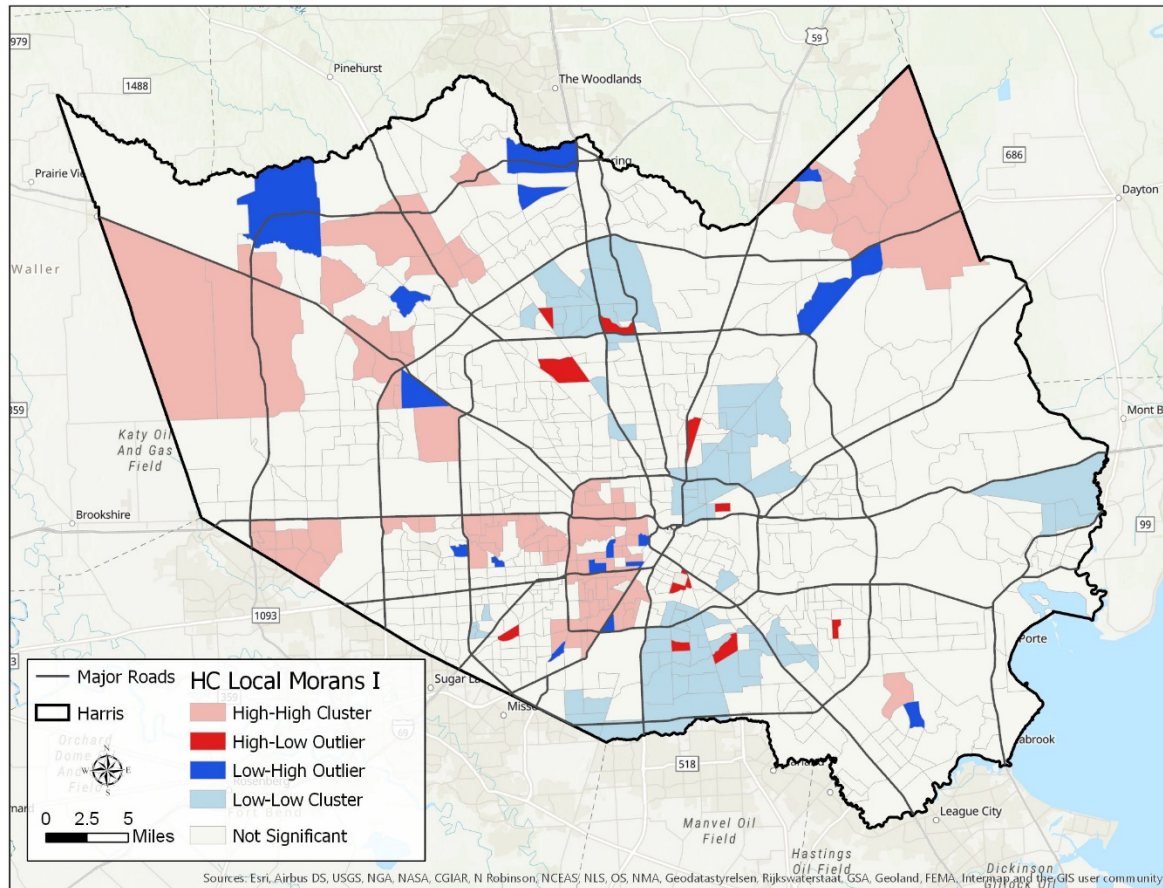
In the state-wide analysis, we found 83 hot outliers, or census tracts with a statistically significant high percentage of SNAP EBNE households, surrounded by census tracts with significantly low percentages of SNAP EBNE households, demarcated as “HL.” We also found 87 cold outliers, or census tracts with statistically significant low percentages of SNAP EBNE households surrounded by census tracts with significantly high percentages of SNAP EBNE households, demarcated as “LH.” When we re-ran the analysis with only

census tracts in Harris County, we again found similar proportions. Of 781 census tracts, 10 were hot outliers “HL” and 16 were cold outliers “LH.”

***Image 1: Texas – Cluster and Outlier Analysis of the Percentage of SNAP EBNE Households, by Census Tract***



***Image 2: Harris County – Cluster and Outlier Analysis of the Percentage of SNAP EBNE Households, by Census Tract***



**Table 1: Cluster and Outlier Analysis of the percentage of SNAP EBNE Households, by Census Tract**

	<b>Texas Census Tracts (N=5,194)</b>	<b>Harris County Census Tracts (N=781)</b>	<b>P-value<sup>a</sup></b>
Hot Spots (High-High Clusters)	627 (12%)	102 (13%)	<0.05
High Outliers (High-Low Clusters)	83 (2%)	10 (1%)	<0.05
Low Outliers (Low-High Clusters)	87 (2%)	16 (2%)	<0.05
Cold Spots (Low-Low Clusters)	529 (10%)	80 (10%)	<0.05
Not Significant	3868 (74%)	573 (73%)	>0.05

<sup>a</sup> P-value was calculated using Anselin's Local Morans I test. Statistical significance was defined as a p-value<0.05.

Compared with all other census tracts in Texas, SNAP EBNE hot spot census tracts had significantly higher household densities, income levels, and lower poverty rates (Table 3). The same held true when we ran the analysis using only the census tracts in Harris County. Conversely, cold spot census tracts, at both the state-level and in Harris County, had significantly lower income levels and higher poverty rates than other census tracts (Table 3). At the county level, however, we did not find statistically significant lower household population densities in cold spot census tracts like we did in the statewide analysis.

**Table 2. Comparison of Hot Spot (HH), Cold Spot (LL) and all other census tracts**

<b>Texas (N = 5194)</b>				
	<b>Cold Spot (LL) N = 529 (10.2%) Median (IQR)</b>	<b>Hot Spot (HH) N = 627 (12.1%) Median (IQR)</b>	<b>AO + HL + LH N = 4,038 (77.7%) Median (IQR)</b>	<b>P-value<sup>a</sup></b>
Household per square mile Missing	1000.0 (312.5, 1745.0) 0	1198.0 (550.0, 2120.0) 0	835.0 (114.0, 1698.5) 0	<0.001
Median household income Missing	\$33,644.00 (\$27,326.00, \$42,749.50) 0	\$91,536.00 (\$68,545.00, \$121,906.00) 12	\$53,947.00 (\$41,762.75, \$70,853.25) 4	<0.001
% Households below poverty Missing	29.8% (21.75%, 38.25%) 0	5.5% (3.3%, 10.4%) 0	14.0% (8.3%, 21.8%) 0	<0.001
<b>Harris County (N = 781)</b>				
	<b>Cold Spot (LL) N = 80 (10.2%) Median (IQR)</b>	<b>Hot Spot (HH) N = 102 (13.1%) Median (IQR)</b>	<b>AO + HL + LH N = 599 (76.7%) Median (IQR)</b>	<b>P-value<sup>a</sup></b>
Household per square mile Missing	1299.00 (917.00, 2063.50) 0	1941.00 (1196.50, 2851.50) 0	1657.00 (953.00, 2408.00) 0	<0.001
Median household income Missing	\$36781.00 (\$29583.00, \$46384.00) 1	\$98929.00 (\$72803.00, \$126998.50) 5	\$53346.50 (\$39459.00, \$75158.75) 1	<0.001
% Households below poverty Missing	24.0% (18.7%, 35.85%) 0	5.5% (3.5%, 9.7%) 0	15.8% (8.3%, 25.7%) 0	<0.001

NOTE: AO = all others; HH = High-High; HL = High-Low; IQR = interquartile range; LH = Low-High; LL = Low-Low.

<sup>a</sup> P-value was calculated using the Kruskal-Wallis test. Statistical significance was defined as a p-value<0.05.

**Table 3. Pairwise Comparisons of Hot Spot (HH), Cold Spot (LL) and other census tracts**

Texas				
Households Per Square Mile				
Sample 1-Sample 2	Test Statistic	Sig.	Adj. Sig. <sup>a</sup>	
HH - AO+HL+ LH	37.749	.000	.000	
LL - AO+HL+LH	6.085	.014	.041	
Texas - Median Household Income				
Sample 1-Sample 2	Test Statistic	Sig.	Adj. Sig. <sup>a</sup>	
HH - AO+HL+LH	348.313	.000	.000	
LL - AO+HL+LH	371.612	.000	.000	
Texas - Percent below Poverty				
Sample 1-Sample 2	Test Statistic	Sig.	Adj. Sig. <sup>a</sup>	
HH - AO+HL+LH	280.692	.000	.000	
LL - AO+ HL+LH	417.771	.000	.000	
Harris County				
Households Per Square Mile				
Sample 1-Sample 2	Test Statistic	Sig.	Adj. Sig. <sup>a</sup>	
HH - AO+HL+LH	67.431	.005	.016	
LL - AO+HL+LH	-51.333	.056	.168	
Median Household Income				
Sample 1-Sample 2	Test Statistic	Sig.	Adj. Sig. <sup>a</sup>	
HH - AO+HL+LH	254.440	.000	.000	
LL - AO+HL+LH	-186.898	.000	.000	
Percent Below Poverty				
Sample 1-Sample 2	Test Statistic	Sig.	Adj. Sig. <sup>a</sup>	
HH - AO+HL+LH	-237.544	.000	.000	
LL - AO+HL+LH	154.419	.000	.000	
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.				

## DISCUSSION

Our findings align with previous research on SNAP participation. First, hot spot census tracts of SNAP EBNE tend to be more densely populated, which parallels research indicating that SNAP-eligible residents in urban areas participate in SNAP at lower rates than SNAP-eligible residents in rural areas (Bailey, 2014). Additionally, we found that hot spot census tracts of SNAP EBNE tend to have significantly higher income levels. This suggests that a lower proportion of SNAP-eligible households in wealthier areas enroll in SNAP compared to poorer areas - an observation that also aligns with prior research. Pinard et al (2017), in their analysis of scientific literature on SNAP enrollment, found research indicating that SNAP-eligible nonparticipants typically have incomes and assets that are significantly higher than SNAP participants, arguing that the “working poor” are failing to enroll in SNAP.

Limitations in this analysis include the use of ACS 5-year 2018 census tract estimates, which are based on 5 years of survey samples in each census tract as opposed to actual counts, which are not available. Since these estimates are based on survey samples taken over 5 years, they may have high margins of error. An additional limitation arises in using the percentage of people at or below 100% of the federal poverty level to estimate SNAP eligibility, as people in Texas are generally eligible for SNAP if they earn at or below 130% of the federal poverty level. Further factors that make it difficult to estimate neighborhood-level SNAP eligibility include state work requirements, disability, and pregnancy stipulations.

While census tracts are the only geography that the US Census Bureau provides SNAP enrollment estimates for, using them as the geographical unit of analysis presents an additional limitation. While they are relatively equal in population, they often vary in geographical size, especially in rural areas. Additionally, they are easily susceptible to the “ecological fallacy,” where estimates at the census tract-level may not reflect what is happening at the household level. Some of the differences seen in this analysis, therefore, could be attributed to factors beyond the variables analyzed. For this reason, this analysis is intended to serve as a starting place for further research.

Despite limitations, the implications of this research are vast. Pinard et al (2017), in their systematic review of literature on SNAP participation, point to studies indicating that greater availability of SNAP assistance offices and longer hours of operation are associated with increased participation rates at the state level. Using spatial clustering methods to understand where there are neighborhood-level clusters of SNAP EBNE households may enable social service agencies and community-based organizations to allocate their resources more efficiently. With additional insight about these neighborhoods, like the fact that they tend to be more urban and have higher incomes than other census tracts, these entities can hone outreach methods and messaging in a manner that can maximize SNAP enrollment.

Maximizing SNAP enrollment is crucial because estimates suggest that each federally funded SNAP dollar generates \$1.79 in economic activity, supporting farmers, food producers, food retailers, and creating jobs (The Houston SNAP Taskforce, 2018). Research also suggests that increasing enrollment in the SNAP program can reduce individual health



care costs. Berkowits et al (2017) found that participation in SNAP was associated with approximately \$1,400 per year per person lower subsequent health care expenditures, using data from low-income adults who participated in the National Health Interview Survey (NHIS) and the Medical Expenditure Panel Survey (MEPS).

Finally, this method of identifying statistical hot spots, cold spots, and outliers of SNAP EBNE by census tract, can be applied to other safety net programs, like Medicaid, the Children's Health Insurance Program (CHIP), and the Women, Infant and Children (WIC) Program. Armed with area-level knowledge of where these programs are lagging in participation, policy makers and advocates can craft precision outreach strategies to ensure better utilization, thus improving population health and reducing costs. Future research should explore clusters and outliers of SNAP EBNE more thoroughly to better understand the geographical nuances and complexities of how food insecurity and SNAP participation relates to other social factors, like housing, household size, and legal status.

## REFERENCES

- Albert, V., & Lim, J. (2019). Spatial Analyses of the Impact of Temporary Assistance for Needy Families on Child Neglect Caseloads During the Great Recession. *Journal of Social Service Research*, 45(1), 59-75.
- Anselin, L. (2002). Under the hood issues in the specification and interpretation of spatial regression models. *Agricultural economics*, 27(3), 247-267.
- Anselin, L. (2005). Exploring spatial data with GeoDaTM: a workbook. Center for spatially integrated social science.
- Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical analysis*, 27(2), 93-115.
- Bailey, J. M. (2014). Supplemental Nutrition Assistance Program and rural households. Lyons, NE: Center for Rural Affairs. Online at [www.ruralhealthweb.org/NRHA/media/Emerge\\_NRHA/PDFs/snap-andrural-households.pdf](http://www.ruralhealthweb.org/NRHA/media/Emerge_NRHA/PDFs/snap-andrural-households.pdf), accessed February, 13, 2017.
- Beamer, P. I., Lothrop, N., Lu, Z., Ascher, R., Ernst, K., Stern, D. A., ... & Martinez, F. D. (2016). Spatial clusters of child lower respiratory illnesses associated with community level risk factors. *Pediatric pulmonology*, 51(6), 633-642.

Berkowitz, S. A., Seligman, H. K., Rigdon, J., Meigs, J. B., & Basu, S. (2017). Supplemental Nutrition Assistance Program (SNAP) participation and health care expenditures among low-income adults. *JAMA internal medicine*, 177(11), 1642-1649.

Chappelka, M., Oh, J., Scott, D., & Walker-Holmes, M. (2017). Food for thought: Analyzing public opinion on the supplemental nutrition assistance program. arXiv preprint arXiv:1710.02443.

Cluster and Outlier Analysis (Anselin Local Moran's I). (n.d.). Retrieved from <https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/cluster-and-outlier-analysis-anselin-local-moran-s.htm>

Dahlberg, T. (2016, April 18). Summer of Maps: Accounting for Uncertainty with Empirical Bayes Smoothing. Retrieved from <https://www.azavea.com/blog/2013/09/05/summer-of-maps-accounting-for-uncertainty-with-empirical-bayes-smoothing/>

ESRI. (n.d.). Modeling spatial relationships. Retrieved from <https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/modeling-spatial-relationships.htm>

The Houston SNAP Task Force. (2018). Closing the SNAP GAP. Houston, TX

Gray, K. F., & Cunnyingham, K. (2016). Trends in Supplemental Nutrition Assistance Program Participation Rates: Fiscal Year 2010 to Fiscal Year 2015 (No. 83167c08face4195ab0168e9f16dffd5). Mathematica Policy Research.

- Khan, D., Rossen, L. M., Hamilton, B. E., He, Y., Wei, R., & Dienes, E. (2017). Hot spots, cluster detection and spatial outlier analysis of teen birth rates in the US, 2003–2012. *Spatial and spatio-temporal epidemiology*, 21, 67-75.
- Kolak, M., Abraham, G., & Talen, M. R. (2019). Peer Reviewed: Mapping Census Tract Clusters of Type 2 Diabetes in a Primary Care Population. *Preventing chronic disease*, 16.
- Krieger, N. (2006). A century of census tracts: health & the body politic (1906–2006). *Journal of urban health*, 83(3), 355-361.
- Mabli, J., & Ohls, J. (2014). Supplemental Nutrition Assistance Program participation is associated with an increase in household food security in a national evaluation. *The Journal of nutrition*, 145(2), 344-351.
- Pinard, C. A., Bertmann, F. M. W., Byker Shanks, C., Schober, D. J., Smith, T. M., Carpenter, L. C., & Yaroch, A. L. (2017). What factors influence SNAP participation? Literature reflecting enrollment in food assistance programs from a social and behavioral science perspective. *Journal of Hunger & Environmental Nutrition*, 12(2), 151-168.
- Ratcliffe, C., McKernan, S. M., & Zhang, S. (2011). How much does the Supplemental Nutrition Assistance Program reduce food insecurity?. *American journal of agricultural economics*, 93(4), 1082-1098.

Schuler, D. A., & Koka, B. R. (2019). Challenges of Social Sector Systemic Collaborations: What's Cookin' in Houston's Food Insecurity Space?.

Shannon, J. (2014). What does SNAP benefit usage tell us about food access in low-income neighborhoods?. *Social Science & Medicine*, 107, 89-99.

Slack, T., & Myers, C. A. (2014). The Great Recession and the changing geography of food stamp receipt. *Population Research and Policy Review*, 33(1), 63-79.

SNAP Food Benefits | How to Get Help. (2019b). Retrieved from Texas.gov website:  
<https://yourtexasbenefits.hhsc.texas.gov/programs/snap>

US Census Bureau. (2019, September 17). When to Use 1-year, 3-year, or 5-year Estimates.  
Retrieved from <https://www.census.gov/programs-surveys/acs/guidance/estimates.html>.

Wheeler, D. C. (2007). A comparison of spatial clustering and cluster detection techniques for childhood leukemia incidence in Ohio, 1996–2003. *International Journal of Health Geographics*, 6(1), 13.